NORWEGIAN SCHOOL OF ECONOMICS

Measuring and Predicting Bond Fund Performance

An Empirical Study of the Norwegian Market

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Abstract

This paper concentrates on the performance of Norwegian bond funds by measuring the risk-adjusted return (alphas) and examining the predictive power of several fund characteristics. We use daily returns both gross and net of expenses on 18 actively managed corporate funds between October 2006 to September 2016. In the first part, the performance is measured by employing a single-index model and several multi-factor models over the full ten-year period. We find that about 70% of bond funds have been able to generate significant abnormal returns gross of expenses. After adjusting for expenses, only about 30% of the funds generate significant out-performance. Moreover, there is not a single fund exhibiting a significant negative performance. A non-constrained multi-factor model that captures the term and default premium best describes the return variation of these funds. In the second part, we test whether abnormal performance can be predicted while accounting for relevant characteristics which can impact the future performance. The analysis is conducted over twenty half-year periods using three multi-factor models. We find evidence that persistence in abnormal return during the current half year period is a significant predictor of abnormal performance over the next half year period. Our analysis reveals approximately a third of the risk-adjusted return over the current period carries forward to the next period. There is an insignificant relationship for all other factors. The result is found to be robust across all multi-factor models.

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Contents

1 Introduction

The Norwegian bond mutual fund industry has grown at a striking pace from NOK 36.8 billion in January 2006 to NOK 317.8 billion in September 2016 (Statistics Norway). Although the investor community has eagerly shown interest by embracing fixed income funds as an investment option, comprehensive academic literature concerning Norwegian bond funds is close to nonexistent. However, international research focusing on bond fund performance has grown considerably as markets within other regions of the world have increased in magnitude at a similar pace as the Norwegian market.[1]

Moreover, recent events within the Norwegian mutual fund market indicate that companies have come under significant public scrutiny for lack of active management. In early 2015, The Financial Supervisory Authority in Norway condemned three DNB funds for being passively managed and thus overcharging fees to investors while stating to be actively managed funds. The matter worsened over the following year when in June 2016, a subpoena was issued against DNB funds after a case was filed by the Consumer Council of Norway. The Consumer Council claimed that DNB had falsely charged NOK 690 Million during the period 2010-2014 by portraying to be actively managed (Forbrukerradet, 2016). As the funds under criticism are equity mutual funds, the question now arises whether investors have gained from seeking active management in the bond fund market? Moreover, are Norwegian bond fund managers following their equity counterparts by charging excessive fees for passive fund management?

In March 2016, Standard & Poors publicly released bond indices that cover the Norwegian investment grade bond market.[2] Similar indices have been the basis of a majority of international research on bond fund performance. Segmented indices allow comparison of fund returns against a benchmark purporting similar risk characteristics. Hitherto, Norwegian bond funds have used government indices as their respective benchmarks, thereby misrepre-

[1]The growth in the bond fund market, in general, can be largely attributed to a larger focus on fixed income securities following the financial crisis in 2008 (Deutsche Bank, 2014).

[2]Examples of bond indices are Norwegian Corporate bond index AAA and Norwegian Corporate bond index BBB. More information about S&P indices will be discussed in section 3.3.

senting the actual risk taken on by a fund within its investments. Any return in excess of the government index could mislead an investor into believing that a fund can deliver abnormal returns.

To our knowledge, only a few unpublished studies have investigated the Norwegian bond fund market. Gjerde & Sættem (1996) evaluated the performance of bond mutual funds from 1992 to 1995. Their study found no significant superior performance at a cumulative level. A more recent study by Kamalanathan & Berge (2016) examined the performance of 22 Norwegian Bond Funds between 2011 and 2015. By using self-created benchmarks, their study concluded that none of the funds showed significant positive performance and that investors would be better off without investing in funds seeking to harvest returns from market timing and security selection. Conclusions from both the papers were drawn based on a monthly data frequency of returns net of expenses.

Though the results from both papers are in line with the financial theory of the efficient market hypothesis, there are certain inadequacies in their approach as suggested by several studies. Goetzman, Ingersol & Incolvic (2000) found shortcomings in the use of monthly data and proposed the use daily data for performance evaluation. Bollen & Busse (2001) indicate that conclusions within the subject of portfolio performance, particularly market timing ability, are sensitive to data frequency. Bollen & Busse (2001) extend this argument and show that higher data frequency enhances model reliability and power.[3] Additionally, the self-constructed benchmarks within Kamalanathan & Berge (2016) use an index creation methodology which excludes bonds with optionality features such as callable and puttable bonds. By doing so, benchmarks fail to capture the behavior bonds with option components, which is an important part of the market (Moneta, 2015). Elton, Gruber & Blake (1995) also highlight that fixed income securities with optionality features take up a substantial part of the market, which should be represented in benchmarks used for performance evaluation.

[3]The argument is also supported by Bodie, Kane & Marcus (2013) and Bessembinder, Kahle, Maxwell & Xu (2009).

1.1 Aim and Research Questions

Motivated by the findings stated in the previous section, we aim to conduct a thorough study of the Norwegian bond fund market. Performance estimation has been the main objective of the studies conducted within this market so far. Evaluating and estimating the performance of actively managed bond funds has important implications for understanding the value of active management. However, no paper has focused on the possibility of foreseeing or predicting an abnormal return of Norwegian bond funds. To be able to predict abnormal performance has important implications from both an investor‘s and an academic perspective. From an investor‘s perspective, it makes it possible to earn an abnormal return by utilizing publicly available information. The academic importance is that predictability of performance reveals an inefficient form of the market. Building on this reasoning, the aim of this study is to understand Norwegian investment grade bond funds by looking at two dimensions of performance, namely estimation and prediction.

In the turmoil of public criticism of asset management companies charging excessive fees for their service, we wish to explore the effect of fees in greater detail by looking at both net and gross returns. In the context of performance evaluation, it can be argued that an investor of an actively managed mutual fund should be expected to pay for the pure alpha, and not for persistent biases towards risk (Dopfel, 2004). With that in mind, we present our first hypothesis:

1. Are Norwegian bond funds able to generate a risk-adjusted return, both net and gross of expenses?

Whether or not mutual funds have been able to generate abnormal returns, it is imperative from an investor‘s point of view to know in advance which funds can. To address this issue we present the second hypothesis:

2. Can mutual fund performance be predicted while accounting for relevant risk exposures?

These questions are aimed to build comprehensive understanding of Norwegian bond funds as an investment option by looking at recent, widely used and highlighted methods within the field of bond and equity portfolio performance. The newly available indices within the bond market enable a comparable study and enhancement of the understanding of Norwegian bond funds. The two dimensions performance estimation and prediction are core to recent research regarding portfolio performance. Therefore, the proposed questions are designed to yield the greatest possible increase in understanding of the specific market in two fundamental ways. Firstly, the models suited to answer the questions are widely used and their accuracy has been evaluated by prominent researchers, thus reducing the ambiguity of our results. Second, the extensive research available applying similar approaches makes it easier to assess the results in comparison with other markets. These aspects will be further explored in the literature review.

1.2 Design and Research Methods

The paper looks at 18 actively managed open-end Norwegian investment grade bond funds during the period from October 2006 to September 2016. A daily data frequency is used to evaluate the performance of the sampled funds. The study is divided into two parts, where each part is suited to answer the individual research questions.

In the first part, the paper focuses on performance estimation by mimicking models that have been applied to the US bond fund market. A return based approach is used to determine a measure of the risk-adjusted return of each fund over the entire ten year period. A return based approach entails using regression analysis to deconstruct the returns of a fund by looking at exposures to a single or multiple indices. The analysis sheds light on the impact of fees by comparing abnormal returns, net and gross of fees. Evaluating performance using gross returns allow us to identify whether any funds have skills in selecting portfolios that outperform relevant benchmarks, and the net returns enable us to determine whether any abnormal performance arising from such skills is transferred across to investors after deducting the fees.

In the second part of the study, the focus shifts towards performance prediction. To test the second hypothesis, we introduce fund characteristics that have been empirically and theoretically supported for having an effect on mutual fund performance, as potential predictors. In this analysis, the dataset is divided into 20 half-year periods to look at the predictive power of the selected fund characteristics. The Fama & MacBeth (1973) procedure is applied to investigate the relationship of predictive characteristics of performance. The methodology closely follows a framework introduced by Amihud & Goyenko (2013).

1.3 Main Findings and Contribution

The results of performance estimation indicate that about 70% of the sampled funds can generate significant abnormal returns before deducting expenses. However, net of expenses only about 30% of the funds are able to generate a significant abnormal return. Therefore, expenses seem to deteriorate risk-adjusted return for a majority of the funds. Moreover, the results indicate that two funds have been able to generate strongly significant abnormal returns that exceed the effect of expenses.

In the analysis of predictive characteristics, we find evidence of short-term persistence as an indicator of future performance. The result implies that performance of funds in the previous half-year period are positively correlated with the performance of current half-year period. The estimates indicate that about a third of the returns are carried over to the next half-year period. Furthermore, persistence is the only factor that significantly predicts the performance of a fund across model specifications.

This study makes a number of contributions to the existing literature within the Norwegian bond fund market. The study is first to investigate bond fund performance with daily data frequency returns for determining fund specific factor exposures based on a ten-year period. Second, the study pioneers the use of the official S&P Nordic benchmark indices. As the indices from S&P include bonds with optionality, our study overcomes the issue highlighted by several researchers. Finally, this is the first Norwegian study to examine the predictability of bond fund performance.

1.4 Norwegian Bond Fund Market

According to the Norwegian Fund and Asset Management Association,[4] there are five main types of mutual funds in Norway. These are Equity funds, Bond funds, Money Market funds, Hybrid funds and Other. Bond funds account for 31.8% of the total market and have the second largest market share. Figure 1 illustrates the recent market share of all mutual fund types in Norway.

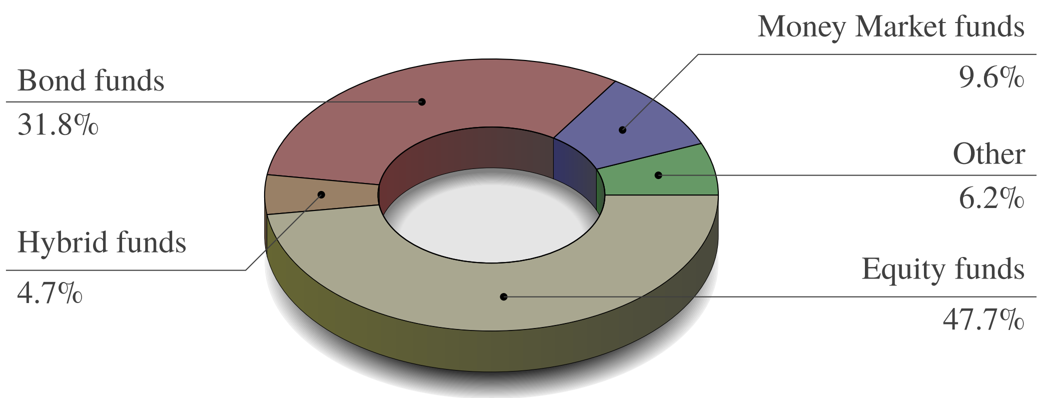

Figure 1: Market Value of Norwegian Mutual Funds, June 30th 2016 (Statistics Norway)

The Norwegian bond fund market has experienced a remarkable growth of inflows in the last decade. From 2006 to 2016, the market has grown at a compounded annual growth rate of 24%. This has resulted in a combined market value of 317.8 billion NOK, as of June 30th, 2016 (Statistics Norway).

Till date, most Norwegian bond funds use a government bond index as a comparative benchmark. Defining a benchmark with the same risk exposures/investment style as the bond fund portfolio is the core of prominent literature focused on performance evaluation. In March 2016, S&P introduced new style indices for the Norwegian Bond Market. Further, more indices were launched in September and October 2016. The new S&P Norwegian indices divide the Norwegian Bond market based on maturity and credit rating. The indices are tailored to act as benchmarks for funds with a particular investment style. Moreover, such indices can be used in two approaches within performance evaluation studies, namely a return-based approach and a holdings-based approach. The return based approach uses

[4]Also known as Verdipapirfondenes Forening (VFF).

portfolio returns of multiple indices and draws inferences about how closely the funds return match with the those of the benchmarks. The holding based analysis uses information about portfolio holdings of the fund and compares the return on individual holdings to the respective indexes. Information about portfolio holdings is not yet accessible in the Norwegian bond fund market. However, fund's net asset values are available, and we will further discuss this in section three.

Furthermore, fund managers are paid number of different types of fees for their service, where the most common is a management fee or expense ratio structured to be paid yearly as a percentage of assets under management. Other fees include load fees and performance fees. Front-end and back-end load fees are costs charged when investors buy into a fund or sell their shares and are calculated as a percentage of the money invested or taken out of a fund. In our sample, only two of the funds currently have load fees, which is representative of the market as a whole. Furthermore, there is also performance fee which is structured as a percentage of the return of a fund and is typically charged on a yearly basis. None of the funds in our sample have this fee structure, although some of the funds excluded from the analysis do. To be precise, management fee or the expense ratio is the only type that will have a direct impact on the return of a fund within our analysis.[5]

The remainder of this paper is structured as follows. Section two provides a literature review covering relevant academic papers on topics similar to ours. Section three presents the dataset used, highlighting the selection criteria and the relevant fund characteristics that were gathered. Section four details the methodology used to address the two hypotheses. Section five shows the empirical results on measuring performance and predicting performance. Section six present the limitations followed by section seven with concluding remarks.

[5]The fee structure of sampled funds can be found in Table 2.

2 Literature Review

We divide the literature into two sections, measuring and predicting fund performance. Each section reviews the empirical theories advanced to test the hypothesis one and two, respectively.

2.1 Measuring Fund Performance

Jenson (1968) was the first to present a risk-adjusted performance framework for evaluating actively managed mutual funds. The study introduced a performance measure, known as the alpha, within the single index model based on the capital asset pricing model (CAPM) presented by Sharpe (1964) and Lintner (1965). By evaluating the performance of 115 U.S. mutual funds between the period 1945-1964, Jenson (1968) found that average returns, net of expenses, were unable to outperform the returns of the market index.

Elton, Blake and Gruber (1993) presented evidence on the incapability of the single factor benchmark to capture cross-sectional variations in bond returns. Their approach implemented the use of multifactor models to conduct the pioneer study on bond mutual funds.[6] Using a sample of U.S. bond funds between 1979 and 1988, Blake et al. (1993) indicate that all funds, except high yield funds, underperform relative to their matched benchmark. Their study states that the failure to assign appropriate benchmarks was the main cause for positive abnormal performance for high yield funds. The paper also concluded that the degree of underperformance for funds was approximately equal to the average management fees, thereby suggesting that the gross return of funds would be on par with the returns on the respective passive benchmarks.

Research on multifactor pricing models accounting for a variety of risk factors were extended by Fama & French (1993). Their study introduced two risk factors associated with

[6]Cornell & Green (1991) conducted a study on the investment performance of junk or low-grade bond funds and , Blume, Keim & Patel (1991) investigated the volatility in returns of low-grade bond funds. However, Elton, Blake & Gruber (1993) was the first comprehensive study which included all types of bond funds.

bonds. First, the common risk in bond returns depends on changes in prevailing interest rates within the market, and the value of a bond will be inversely related to interest rate changes. The value of a bond can be viewed as the sum of discounted future cash flows. As a result, bonds with a longer duration will disproportionately be affected as the risk of rate variations increase with time. Fama & French (1993) asserted such a risk factor as TERM. The factor was calculated as the difference between the monthly long-term government bond index and the one-month Treasury bill rate measured at the end of the previous month. Second, fluctuations in economic conditions can change the likelihood of default on corporate bonds. Moreover, the value of a bond with a low credit rating will be lower as the probability of the issuer not to meet the payment obligations is higher. Fama & French (1993) use a proxy for this risk factor called DEF. The default factor was calculated as the difference between the long-term corporate bond index and the long-term government bond index. Their study concluded that the two factors had the ability to explain average returns of fixed income securities.

In addition to the term and credit risk factors, Bodie, Kane & Marcus (2013) point out several other factors which complicate risk calculations in bond returns. The most prominent are the ability to have a call or put option within the lending agreement. A callable bond enables the issuer to repurchase the bond at a predefined price before maturity. A callable bond will decrease the upside for an investor, as a rational issuer will repurchase the bonds in case interest rates fall below a certain point and will issue new ones. In contrast, a put option will increase the upside of a bond as it enables the owner to extend the life of a bond in case the coupon rate of a bond exceeds the current market yield. A general implication of optionality within bonds is that duration becomes a conditional variable and this will have implications for interest rate risk calculations. Therefore, it is important for performance evaluation studies to consider benchmarks which include bonds with options. The impact that optionality has on risk is difficult to quantify. However, the effect of term and credit risk can be quantified by attributes such as time to maturity and credit rating.

Sharpe (1992) coined the term style analysis[7] as a framework to measure the performance

[7]Sharpe (1988) earlier defined the term as an effective asset mix analysis. A method that derives inferences on the portfolio composition, using a constrained regression, based on past returns.

of mutual funds. The framework has specific requirements and is applicable in three forms. The paper states that factors must be indices that preferably are mutually exclusive, exhaustive and has returns that differ. The broader idea was to compare mutual fund returns with a basket of indices, which have the same style and represent the entire investment universe of a fund. The three forms of style analysis include weak, semi-strong and strong. The weak form is essentially an unconstrained regression that fulfills the required factor characteristics. The semi-strong imposes a restriction that the sum of factor loadings should equal to one, implying that the funds can not represent more than 100% exposure across the indices. The strong form includes the restriction of the semi-strong form along with another restriction where each factor loading should be non-negative. The reasoning behind these restrictions is to conform to the investment policies of the fund. Imposing the restrictions effectively makes it certain that the benchmark can not be calculated by gearing or shorting any of the individual bonds. Therefore, the calculation of the benchmark conforms to how a mutual fund operate. The paper proposes the restrictions might lead to more efficient results. This argument has been supported by a variety of later studies such as Horst, Nijman & Roon (2004).

Kahn & Rudd (1995) used return based style analysis (strong form) to shed light on persistence within the US mutual fund market. The fund's style weights/components were calculated based on two out of sample periods. The study finds evidence of persistence in returns of fixed income mutual funds beyond effects of fees and expenses. The paper also compares the effect of expenses by using both a net and gross return series as dependent variables.[8] However, the results indicated that the total effect of fees does not overcome the average underperformance of funds.

Elton, Gruber & Blake (1995) developed relative pricing models that incorporate both return on relevant indices and unexpected changes in fundamental economic variables. By doing so their study found that index returns were the most important factor in explaining returns on bond funds. Their choice of indices included most parts of the bond fund market. Similar to the Fama & French (1993) five-factor model, they include term and default as the main risk factors in bond returns.

[8]The paper calculates the gross return series by adding back expenses taken from a fund's assets.

Horst, Nijman & Roon (2004) suggested that return-based style analysis performs better than holding-based style analysis in predicting future fund returns. The main point is that holding based analysis does not appropriately estimate investment style, because of cross exposures between asset classes. Dopfel (2004) discussed the concerns of fixed income style analysis and proposed that a manager's investment process, historical performance and the types of bets a manager makes can be useful to inform about expected alphas.

Dietze, Entrop & Wilkens (2009) used a return based approach and presented evidence on the performance of European investment grade bond funds. By including both rating-based and maturity-based indices in multifactor models their study finds that not a single fund exhibited significant abnormal performance. Mason, McGroarty & Thomas (2012) used newly issued style indices from S&P to evaluate various return based style methods within the US market. Their study concluded that return based style analysis could be useful in conducting performance evaluation and for providing historical information on the risk exposures of a fund.

Bessembinder, Kahle, Maxwell & Xu (2009) applied a single factor and several multifactor models in a study about the robustness of pricing models. These models included a modified version of the earlier introduced Elton et al. (1995) model and the five-factor model by Fama & French (1993). Also, they proposed a new multifactor model that relied on indices characterized by a specific maturity and credit rating. By simulating shocks[9] in the market for both daily and monthly price data, they suggest that use of the new multifactor model appropriately captured the risk-adjusted returns. They argue that both estimates and inference measures were superior, as opposed to the other models in the study. Furthermore, they suggest that the use of monthly data severely biases both estimates and inference measures, as they are unable to capture movements in the market. The study argued that while measuring abnormal bond performance, there underlies credibility in reexamining studies previously conducted using monthly data with daily data.

[9]The shocks are introduced to represent corporate events.

Despite genuine evidence in the merits of using daily data, conventional mutual fund research over the past decades has been undertaken using monthly data. Busse (1999) pioneered the use daily data within mutual funds and found evidence that by using daily returns, mutual funds were able to reduce market exposures and increase risk-adjusted returns timely. Goetzmann, Ingersoll & Ivkovic (2000) showed that the lower power to detect timing skill was due to a downward bias arising from the use of monthly returns. Bolle & Busse (2001) documented a higher market timing ability in daily tests than monthly tests.

Furthermore, several studies have shed light on the effect of expense ratios by using gross returns and net returns to examine mutual fund performance. Elton et al. (1993) documented a negative relationship between expense ratio and performance. This argument was later supported by Carhart (1997) who finds the negative effect of expense ratios on performance to be slightly higher than one-for-one. Malkiel (1995) found that mutual funds tend to underperform the market gross of expenses excluding load fees.[10] So far studies prove that expense ratios are often an insurmountable obstacle to beating a benchmark. Wermers (2000) conducted an exhaustive study of U.S. mutual funds and concluded that the funds outperform the market gross of expenses. However, after accounting for transaction costs, expense ratio and returns on non-stock holdings, he finds that funds underperform the market net of expenses. Similarly, Chen, Ferson & Peters (2010) find that on average bond mutual funds returns outperform the returns on passive indices on a gross level but underperform on a net level. Fama & French (2010) use the three and the four-factor model to compare the effect of fees on U.S. equity mutual funds. Their study indicates that only a few funds earn back the fees charged to investors. While calculating the gross return, Fama & French (2010) argued that the implications of not being able to look at the front and back-end load fees as well transaction costs are negligible.[11] Moneta (2015) highlighted that active fund managers were, on average, able to generate one percent per annum over the benchmark portfolio, thus suggesting that managers were able to earn back their fees and costs. His study covers the U.S. bond funds during the period 1997-2006 and used an abbreviated holding-based style analysis.

[10]For more studies documenting the negative effect of fees, see Golec(1996), Dahlquist, Engstrom, & Soderlind (2000), among others.

[11]Fama & French (2010) define gross returns equal to net returns plus expense ratios.

2.2 Performance Prediction

In this section, we highlight the literature that examines the effect or predictive power of specific characteristics on fund performance. We review the literature to reason the methodology used to test hypothesis 2. This methodology will largely follow one specific framework introduced by Amihud & Goyenko (2013). However, this paper contributes incrementally to a field of research that has evolved through many papers.

Carhart (1997) conducted one of first comprehensive studies on fund characteristics to determine the effect of age, expense ratio, size, turnover and persistence on mutual fund performance. The paper finds a significant persistence in mutual fund returns. The main finding indicates that if an investor buys the top decile funds and sells the bottom decile funds based on returns, the investor would yield 8% return next year. Furthermore, the paper suggests that expense ratio and turnover have a significant negative relationship with performance. However, the effect of size and age were found to be insignificant.

Huija & Derwalla (2008) find a significant persistence in US bond funds which is robust throughout a variety of model specifications and bootstrapped test statistics. Furthermore, Du, Huang & Blancfield (2009) examine the short-term persistence in high-quality bonds. Their study concludes evidence in support of short-term persistence, which is in line with Bollen & Busse (2005). The degree of abnormal return is equal to the fee charged, and the funds do not seem to have a significant level of net abnormal returns.

Dahlquist, Engstrom, & Soderlind (2000) investigated the cross-sectional effect of performance with fund size, fee, turnover and past performance for Swedish mutual funds.[12] The study concluded that smaller funds were related to good performance. On the contrary, Otten and Bams (2002) conclude that there is a positive relationship between size and performance, while examining the effect of age, expense ratio and size on European equity funds.[13]

[12]In their paper, the sample set consisted of equity, bond and money market funds.

[13]Otten & Bams (2002) also concluded that the funds delivered positive risk-adjusted performance after expenses, a result contrary to most US studies.

Dietze et al. (2009) investigated the impact of fund characteristics such as age, size and expense ratio and management tenure on performance and found that older funds and funds charging lower fees attained higher risk-adjusted performance. In a study by Otten & Bams (2002), they observed a negative relationship between age and performance whereas Low (2010) and Bialkowski & Otten (2011) report no indication of significant relationship. A majority of recent research uses age as a control variable and have found an insignificant relationship.

Chen et al. (2004) conducted a cross-sectional analysis on mutual funds to analyze the effect of fund size on performance. The paper reveals that fund returns decline with lagged fund size, before and after fees. This effect may be associated with organizational diseconomies arising from uncontrolled growth in size. More recently, a general approach to look at the relationship between fund size and performance was introduced by Bodson, Cavenaile & Sougné (2011). The study aims to do one cross-sectional regression on alphas using both a linear and quadratic independent variable.They find a concave relationship between total net assets and performance and therefore suggest that there is an optimal medium size of a fund.

Amihud & Goyenko (2013) use daily prices for US mutual funds to test the predictive power of R-squared, for both the equity and bond market. They use a logarithmic transformation of R-squared as a proxy for selectivity. To estimate the alphas and R-squared, they use the pricing models by Elton et al. (1995) and Bessembinder et al. (2009). They also use other control variables such as age, expense ratio, turnover, size and management tenure in their study. By testing the relationship of all variables on performance in a Fama & MacBeth (1973) procedure, the paper states that performance of the funds significantly goes down as the preceding R-squared increases.[14] The study presented evidence of half yearly persistence within returns on bond funds. Moreover, there is an insignificant relationship for other control variables for bond funds. While the main focus of the paper is to look at selectivity as an additional factor, the other factors tested are chosen based on the findings from the earlier

[14]This relationship was found for the equity mutual funds, whereas for bond funds there was an insignificant relationship.

mentioned papers. Overall, the paper presented by Amihud & Goyenko (2013) is a result of the collective findings and evolution of research on fund characteristics.

The approach exhibited by Amihud & Goyenko (2013) is comprehensive in determining the predictability of mutual fund performance, and we will apply their approach in our study to test whether bond fund performance can be predicted within the Norwegian market. One point that differentiates the paper from a majority of research within this field is that an estimate of risk-adjusted return is used as a metric of performance, as opposed to the direct return.

3 Data

In this section, we present the data used for conducting the empirical analysis of this study. Each subsection provides a complete overview of sources and data collected. At the end of each subsection, the data is organized in order by their use in the methodology section.

3.1 Bond Mutual Funds

Our primary data set consists of bond mutual fund prices spanning over a ten-year period between October 2006 and September 2016. Information about the type and number of mutual funds in the Norwegian market is gathered from the MorningStar website. For a fund to be included in the analysis, we define the following selection criteria based on relevant academic practice.

I. The fund must have a focus on the Norwegian investment grade corporate bond market.[15]

II. The fund must have a minimum 90% exposure to bonds.

III. The fund must have a minimum of NOK 20 million assets under management (AUM).[16]

[15]Following Elton et al.(1993), we exclude all government, high-yield, hybrid, or internationally focused funds.
[16]Elton et al. (1993) excludes small funds as they may have different reporting practices and Chen et. al (2010) highlights that small funds are subject to backfill bias.

IV. The fund must follow an active investment strategy, and all passively managed funds shall be excluded.

This results in the final fund sample of 18 actively managed bond funds[17] over the ten-year analysis period. The funds represent NOK 52 billion assets under management as of September 30, 2016. Descriptive statistics of the selected funds is included in Table 1.

3.2 Net Asset Value

Our primary data source for collecting daily net asset values (NAV's) for each fund is MorningStar Direct (MSD). To get valid and reliable results, the accuracy in daily return series is important. The problem with inaccurate daily data points was highlighted by Bessembinder et al. (2009). We thoroughly reviewed the quality of data by further gathering prices from three different sources - Amadeus[18], Bloomberg and Reuters Datastream (henceforth referred as other databases).

Data review

The data set from MSD was most comprehensive in reporting daily prices as compared to other databases. The initial data gathered from MSD had a total of 2609 daily NAV's for each fund during the ten-year period. The crosschecking of data with the other databases revealed two main elements about daily prices. First, there were questionable data points on certain days for which prices reported against all funds matched with prices of the previous days. On further investigation, we find that such days were not reported within the data set collected from other databases. Consequently, we labeled these days as non-trading days and removed them from the data set. This resulted in dropping 108 non-trading days, which was approximately 4.2% of the NAV's initially gathered. Second, on examining the remaining 2501 NAV's for the 18 funds, we find 160 missing NAVs across the entire sample of funds.

[17]Though this sample size appears small, Horst et al. (2004) used 18 funds within their analysis to evaluate mutual fund performance.

[18]Amadeus or Børsprosjektet is a data service which collects data from Oslo Børs, and is operated at the Norwegian School of Economics (NHH).

The missing prices were more prevalent in the early years of the analysis period. The missing prices were then filled after referring to two other databases, Amadeus and Datastream. We ended up filling 160 prices across the 18 funds, which accounts for 0.4%[19] of the fund sample for the entire period. Subsequently, no fund had greater than 2% of the 2501 NAV's gathered from other databases.

Net returns

The gathered NAV's across the time period were net of dividends and expense ratios. The dividend payment history was gathered for all funds using MSD. The dataset comprising of ex-dividends was accurate and comprehensive for all funds within the MSD database as compared to other databases. We reinvest the dividends by adding them back to the NAV's on the payment date for each respective fund. The daily returns for each fund are calculated as follows:

$$r_{i,t} = \frac{NAV_{i,t} + D_{i,t} - NAV_{i,t-1}}{NAV_{i,t-1}} \tag{1}$$

where $r_{i,t}$ is the daily return of fund i on day t, $NAV_{i,t}$ is the net asset value, and $D_{i,t}$ is the ex dividend of fund i for day t. In total, the final dataset comprises of 45,018 observations of daily returns over the period of ten years.

Gross returns

To be able to compute the gross return, we need to add back the expense ratios to the net returns of each fund. The expense ratio comprises of operating costs such as management fees and other expenses and is usually charged to investors on a yearly basis. The expense ratios for all the funds are collected from both MSD.[20] In line with Fama & French (2010), we abstain from including transaction costs and consider them to have a negligible impact on the analysis. The gross return is computed correcting for the expense ratio, where the yearly expense ratio is divided by the number of trading days (250) per year and added to the net

[19]This is calculated by $160/(18 * 2501) = 0.4\%$, rounded off to the nearest decimal.

[20]The MSD database collects the expense ratios from the prospectus of each fund. We crosschecked the expense ratios with the prospectuses and found them to be correct within the dataset.

return of a fund. Hence, we get

$$Gross\ Return_{i,t} = r_{i,t} + \frac{EXP_{i,year}}{250} \tag{2}$$

3.3 Benchmarks Indices

The overall objective of style analysis is to find an appropriate benchmark to compare the given portfolio return on funds. By doing so, we can calculate the risk-adjusted return of a fund. Currently, all sampled funds have self proclaimed benchmarks that are government bond indices, as presented in Table 1. Ang (2014) highlights that self-designated benchmarks may not be the best measure in mutual fund performance evaluation.

We select benchmarks that can represent characteristics of all parts of the market. The data for a wide range of indices is collected from the S&Ps website. For all indices, the price data is available as far back as September 2006 and our study period of ten years reflects the complete availability of the index time series. Further, the style indices divide the Norwegian corporate bond market into different classes of risk, which can be classified as credit rating and maturity classes. The Norwegian Investment Grade Corporate Bond Index and the Sovereign Bond Index are used as risk factor proxies for the entire market and the low-risk market, respectively. In addition to newly published indices by S&P, we include one index published by Oslo Stock Exchange (Oslo Børs). Table 2 shows the complete list of indices used within each model.[21] The returns on indices are calculated using the following formula:

$$r_{m,t} = \frac{Index_{m,t} - Index_{m,t-1}}{Index_{m,t-1}} \tag{3}$$

where $r_{m,t}$ is the daily return of the benchmark m on day t, and $Index_{m,t}$ is the daily price of the benchmark.

[21]We will elaborate the relevance of each index within different models in the methodology section.

3.4 Risk Free Rate

NIBOR is the only relevant reference rate available in Norway. We include the three-month NIBOR rate [22] as a measure of the risk-free rate. The rates for the ten-year period are collected from the Oslo Børs database (The rates were cross-checked with Reuters Datastream). The instrument is reported as an annualized three-month nominal rate. Annualized rates on short-term investments are often reported using simple rather than compound interest (Bodie, Kane & Marcus, 2013). Furthermore, the factsheet for the NIBOR calculation states a simple annualized return (Oslo Bors, 2014). Therefore, calculation of the daily risk-free rate is computed by dividing the annualized rate by 250.[23]

Daily excess returns

In accordance with CAPM and academic practice, our study relies on computing excess returns for each fund and index. By deducting the daily risk free rate from the daily returns on funds and benchmarks we obtain the daily excess returns. Following Bodie et al. (2013) the excess returns can be denoted by the following equations:

$$R_{i,t} = r_{i,t} - rf_t \tag{4}$$

$$R_{m,t} = r_{m,t} - rf_t \tag{5}$$

where, $R_{i,t}$ is the daily excess return on the fund i on day t, and $R_{m,t}$ is the daily excess return on the benchmark m on day t.

3.5 Fund Characteristics

A priori it is unknown which factors can affect fund performance. To shed light within this area, we model risk adjusted return as a function of factors that have been empirically supported to have an effect on performance. The factors applied within the cross sectional

[22] Bolle & Busse (2005) use a three-month treasury bill and scale it down to daily risk-free return.

[23] As the variance of returns is very low over non-trading days compared to trading days, use of trading days (250) is recommended (Hull, 2006). This also corresponds well with the number of days in each year in our dataset.

study are fund and time specific and are gathered from pricing models as well as external sources. The factors gathered from external sources include age, expense ratio, fund size, and factors from pricing models are alpha and R^2.[24]

The age of the fund is forgathered from the prospectus of each fund. The information about the inception date is found on the summary page of the prospectus. The age is computed by deducting inception date from the beginning date of the analysis. The fund size has been collected from MSD. We extract fund size on a daily basis to efficiently capture the changes in fund size across the time frame of analysis. The frequency of reporting fund size varies across funds. However, there were sufficient half-year data points to give an estimate of the fund size during every period. The expense ratio collection has been discussed earlier.

For the purpose of our analysis, each factor value is computed as an average of available datapoints within a non-overlapping 125-day rolling window (half year). The dates on which these datapoints are set to be computed are based on gathering half year data from 2006-2016. This implies that each factor is computed for twenty half yearly periods. As a result we gathered a panel data set comprising of 360 $(20 * 18)$ data points for each factor across the 18 funds.

[24]The factors gathered from pricing models will be discussed in section five.

Table 1: Descriptive Statistics for Norwegian Bond Funds

	Size	Age	*Fee Structure*		*Returns*			Current
			Expense Ratio	Load Fee	Mean	Median	St Dev	Benchmark
Alfred Berg Lang Obligasjon	160	18.47	0.60	0	5.53	5.73	41.68	ST5X
Alfred Berg Obligasjon	2,885	21.21	0.60	0	4.52	4.55	25.95	ST4X
Carnegie Obligasjon	332	23.23	0.35	0	4.55	4.60	29.97	ST4X
Danske Invest Norsk Obligasjon	898	18.04	0.49	0.35	4.70	5.14	27.95	ST4X
DNB Kredittobligasjon	2,581	7.32	0.20	0	5.19	5.36	25.26	ST4X
DNB Lang Obligasjon 20	1,486	9.90	0.20	0	5.44	6.38	42.01	ST5X
DNB Obligasjon	699	23.05	0.62	0	4.76	5.16	24.99	ST4X
DNB Obligasjon (III)	6,665	14.13	0.20	0	5.18	5.58	25.11	ST4X
DNB Obligasjon 20	746	24.52	0.50	0	4.53	4.68	26.02	ST4X
DNB Obligasjon 20 (II)	160	16.00	0.35	0	4.67	4.81	26.01	ST4X
DNB Obligasjon 20 (III)	519	10.33	0.20	0	4.82	4.95	26.02	ST4X
DNB Obligasjon 20 (IV)	6,281	7.32	0.15	0	4.88	5.01	26.13	ST4X
Handelsbanken Obligasjon	508	9.95	0.45	0.2	4.82	5.32	48.49	ST5X
KLP Obligasjon 3 year	439	17.49	0.18	0	4.36	4.48	25.95	ST4X
KLP Obligasjon 5 year	455	17.16	0.19	0	5.46	5.57	44.26	ST5X
Nordea Obligasjon II	2,005	19.24	0.20	0	4.56	4.74	27.33	ST4X
Nordea Obligasjon III	1,827	6.56	0.16	0	4.83	5.12	26.76	ST4X
Pareto Obligasjon	315	12.21	0.46	0	3.45	2.74	22.19	ST4X
Average	1,609	15.34	0.34	0.025	4.79	5.21	27.75	-

This table presents summary statistics of Norwegian investment grade funds in our sample. The data for the fund characteristics are reported with size (MNOK), age (years), annual expense ratios (%) and load fee (%). MorningStar Direct reports the main fund characteristics of our fund sample for the evaluation period from October 2006 to September 2016. The lifetime of a fund is calculated as the difference in days between the date of inception and the and the date of beginning for the analysis. The returns for the funds are reported with daily observations. The table also shows the "Mean" return "Median" return and "StanDev" of fund-specific time-series averages. The ST4X and ST5X indices under current benchmark are government indices.

Table 2: Descriptive Statistics for Norwegian Bond Indices

Indices	Mean	Median	St Dev
S&P Norway Investment Grade Corporate Bond Index	4.59	4.87	27.16
S&P Norway AAA Investment Grade Corporate Bond Index	4.03	3.65	25.78
S&P Norway AA Investment Grade Corporate Bond Index	4.07	3.81	24.96
S&P Norway A Investment Grade Corporate Bond Index	4.77	5.03	31.15
S&P Norway BBB Investment Grade Corporate Bond Index	5.62	4.69	41.03
S&P Norway 10 + Year Investment Grade Corporate Bond Index	6.64	6.89	95.57
S&P Norway 5-10 Year Investment Grade Corporate Bond Index	6.18	6.36	58.70
S&P Norway 3-5 Year Investment Grade Corporate Bond Index	5.10	5.19	32.90
S&P Norway 0-3 Year Investment Grade Corporate Bond Index	3.67	3.35	12.74
S&P Norway Sovereign Bond Index	4.18	5.46	46.28
Oslo Børs Government Bond Index 0.25 Year	2.31	1.53	3.35
S&P Norway Sovereign Bond 1-5 Year Index	3.35	3.66	33.16
S&P Norway Sovereign Bond 5-10 Year Index	5.45	7.95	74.53
S&P Norway Sovereign Bond 7-10 Year Index	5.82	7.75	86.84
Oslo Børs Stock Benchmark Index	7.84	25.44	408.30

The table presents summary statistics for the bond return indices used in the factor models. All of the bond indices and corresponding return data are obtained from S&P's website, with an exception of the Oslo Børs indices which are collected from Børsprosjektet. The index return data are daily and covers a ten year time period from October 2006 to September 2016. The table shows the "Mean" return "Median" return and "StanDev" of index-specific time-series averages.

4 Methodology

This section presents the methodology to test both the hypotheses stated in the introduction. The section is divided into two parts whereby the first subsection presents the methodology for estimating bond fund performance and the second subsection describes the methodology used for predicting bond fund performance.

4.1 Estimating Bond Fund Performance

We present four models from prominent international research on fixed income portfolio performance evaluation. Each model is tailored based on available data and findings within recent literature. Following we elaborate on the theoretical background and application of each model.

4.1.1 Single Index Model

The model presented by Jenson (1968) is based on the Capital Asset Pricing Model presented by Sharpe (1964). The single index model captures the alpha or the fund's excess return after adjusting for the systematic risk (i.e. beta) and the excess return of the benchmark representing the aggregate market. We define the S&P Aggregate Corporate Bond Index as a proxy for the aggregate market that the funds can invest within. The intercept of the model is denoted by alpha and presented in the following equation:[25]

$$\mathtt{R} = \alpha + \beta \, \mathtt{R}_{\mathtt{Corp}} + \epsilon \tag{6}$$

R is the excess return of the fund, α is the risk-adjusted return on the fund, β is the systematic risk, and ϵ is the error term which represents the idiosyncratic risk unexplained by the model. CORP is defined as the S&P aggregate corporate bond index representing the complete market.

[25]Henceforth, for easier readability, we conceal all fund and time subscripts.

Even though it is common practice to use the single factor model, there are certain limitations within the dynamics of this model. Empirical studies show that the use of one market index may not be sufficient in capturing the risk across the bond market (See Eton et al. (1993)). Fama & French (1993) argued that default premium and term premium are the main risk factors that fixed income securities represents. Taking into consideration the influence of these two risk factors has been core to some recent studies (See Boney, Comer & Kelly (2009) and Ayadi & Kryzanowski (2011)). As a result, these factors will be the primary focus in the following multi-factor models.

4.1.2 Elton et al. Model (1995)

Elton et al. (1995) presented a multi-factor model which consisted of factors representing the market risk, term risk and default risk. Also, the model included factors representing unanticipated changes in macroeconomic variables. The original model is presented in equation (7).

$$\mathtt{R} = \alpha + \beta_1 \mathtt{R}_{\mathtt{bond}} + \beta_2 \mathtt{R}_{\mathtt{stock}} + \beta_3 \mathtt{DRP} + \beta_4 \mathtt{TERM} + \beta_5 \mathtt{GDP} + \beta_6 \mathtt{CPI} + \epsilon \tag{7}$$

The macroeconomic factors included within this model were calculated as the difference between the expected values and the realized values of inflation and real Gross National Product (GNP).[26] The stock market factor is a proxy for general economic conditions, while the bond index and risk factors represent exposures within the bond market. In this way, the model developed insights on active management by including fundamental economic variables alongside benchmark returns.

We aim to apply a modified version of Elton et al. (1995) introduced by Bessembinder et al. (2009). The modification of the model focuses on capturing the sensitivities in returns originating from stock market, bond market, term risk and default risk and excludes the macroeconomic variables. The paper by Bessembinder et al. (2009) states that the power

[26]These values were derived based on surveys from forecasters and consumers.

of the model remained intact even without incorporating changes in inflation and GNP. The same observation was highlighted by Gutierrez, Maxwell & Xu (2007) as they find that goodness of fit does not change by excluding the macroeconomic variables.

In the same way as the difference between the returns on small stocks in excess of the returns on big stocks offer proxies for the theoretical risk factors in the Fama & French (1993) equity universe, the difference between long-term government bond and the short-term government bond can offer information on the term structure of interest rates. Bessembinder et al. (2009) includes the difference between long term and short-term US government bonds ($TERM$), the difference between government and corporate bonds (DRP), the return of the Lehman Corporate Bond Index (R_{bond}) and the CRSP value-weighted stock market index (R_{stock}). We apply the Elton et al. (1995) model expressed in equation (8).

$$\mathtt{R} = \alpha + \beta_1 \mathtt{R}_{\mathtt{CORP}} + \beta_2 \mathtt{R}_{\mathtt{Stock}} + \beta_3 \mathtt{DEF} + \beta_4 \mathtt{TERM} + \ + \epsilon \tag{8}$$

For the Norwegian Bond fund market, the model accounts for the Aggregate Corporate Bond Index (represented by $CORP$), Oslo Stock Exchange Equity Index (represented by OSX), the difference between the Aggregate Corporate Bond Index and the Sovereign Bond Index (represented by DEF), and the difference between the 7-10 year and fixed 0.25 year Sovereign Bond Index represented by $TERM$, as independent variables.

4.1.3 Bessembinder et al. Model (2009)

Bessembinder et al. (2009) assigned self-constructed indices within a maturity and credit model used for evaluating the bond market. The constructed indices were distinguished based on the maturity of 0-5, 5-10 and 10+ years and credit rating classes of AAA, AA, A and BBB. A combination of these indices resulted in a 16-factor model where each factor was represented by an index characterized by a specific maturity and credit rating.[27] The matching portfolio technique used rested upon the study conducted by Ho et al. (2005) which assigned

[27] In some instances, the paper reasoned for reducing the maturity division as a result of a small sample base within a given credit rating. This would also be the case if we would segment the Norwegian bond market to that extent.

benchmarks by style weights for determining performance. Furthermore, Bessembinder et al. (2009) concluded that the power of the maturity and credit rating model in explaining performance was the most robust, as opposed to other widely used pricing models. The paper argues that both estimates and inference measures were more accurate at capturing changing market conditions.

Because of the availability of indices in the Norwegian market, we aim to imitate the maturity and credit rating model introduced in Bessembinder et al. (2009) in two approaches. Both will capture the same risk factors as presented in Bessembinder et al. (2009). However, the models will differ in their focus on either time to maturity or credit rating. A similar methodology can also be seen in Dietze, Entrop & Wilkens (2009).

We use the maturity model, as presented in equation (9). The index selection methodology is similar to Bessembinder et al. (2009) by dividing the fixed income market into four risk classes based on the time to maturity of each bond.[28] The inclusion of maturity based indices accounts for term risk differences in fixed income securities. We also include the Government Bond Index which, in interaction with the other indices, acts as a proxy for credit risk premium. This is reasoned by the higher inherent default probability within corporate bonds as compared to government bonds. The division of risk classes allows the complete coverage of the investment grade bond market in Norway.

$$\mathtt{R} = \alpha + \beta_1 \mathtt{Corp}_{0-3} + \beta_2 \mathtt{Corp}_{3-5} + \beta_3 \mathtt{Corp}_{5-10} + \beta_4 \mathtt{Corp}_{10+} + \beta_5 \mathtt{Sov} + \epsilon \qquad (9)$$

The style indices included are S&P Norway investment grade benchmarks and are characterized by maturity period of 0-3, 3-5, 5-10 and 10+ years. By introducing indices constructed by a widely recognized index provider, we avoid constructing bond portfolios and reduce ambiguity in our results.[29]

The other approach used to mimic the model introduced in the paper is based on indices

[28]An important risk factor in bond market, from a fixed income investors' perspective, is duration. Higher duration implicates a greater exposure to interest rate sensitivity.

[29]Ang (2014) stated that trusted index providers are preferred in model construction.

characterized by credit rating. Since the models have a similar construction, only one of the models will be reported in the empirical results. This is done after interpreting and comparing the results of the two approaches.[30]

4.1.4 Quadratic Programming Bessembinder et al. (2009) Model

Recent mutual fund performance studies include restrictions to conform to the basic investment process of a mutual fund (See Matallin, Soler & Ausina (2016)). This methodology originates from Sharpe (1992) and the fundamental idea is to impose restrictions on leverage and short positions. As defined by the mutual funds within our sample, fund managers are often constrained to buying and holding securities within a predefined set of asset classes along with being constrained by their inability to take on short positions and gear their investments. This is also the focal point that differentiates mutual funds from hedge funds.

On the fundament of quadratic programming methodology (QP), we restrict the earlier introduced Bessembinder et al. (2009) model in order to capture the investment style of bond fund manager throughout the analysis period. The beta's calculated by the model mentioned above will represent market exposures experienced by funds. However, as the bond mutual funds are restrained to the degree they are able to short and gear their investments, imposing the constraints and the use of the strong from of style analysis can lead to more efficient estimates as compared to the weak form of style analysis (Horst et al. 2004).

Bessembinder et al. (2009), within their study, used the weak form of style analysis as no restrictions were imposed on the regression. However, we impose restrictions on leveraging and short positions to better tailor the model to how the funds actually operate, as suggested by Sharpe (1992). The model uses a quadratic programming scheme to estimate risk-adjusted returns and factor loadings. Kahn and Rudd (1995) also suggested that the restrictions can lead to more efficient results.[31] We add this model to compare the results with the unre-

[30]We present the results from the maturity model in subsection 5.1.3. The results of the credit rating approach can be found in Appendix 3.

[31]This model is especially interesting to use in the next section of predictive analysis, as Bodie et al. (2013) suggested that it might bias the results in long time periods.

stricted model and to add robustness to our analysis. Also, we get a clear picture of the market exposures experienced by each fund.

In line with Sharpe (1992), below we present the restrictions applied to the Bessembinder et al. (2009) model.[32] This implies restricting β's to be non-negative and that they sum to one. Making the restriction $\beta_j \geq 0$ ensures that none of the funds can have a negative exposure to any part of the market, which implies that funds are unable to hold short positions. Summing the β to one ensures that a fund must have 100% exposure within the market indices, which implies that funds are unable to gear their positions. More precisely, the constraints imply that the benchmark cannot be calculated by gearing or shorting the indices. To be able to apply these restrictions, we present the quadratic programming scheme used to calculate the factor loadings below.

$$\begin{aligned} & \underset{\alpha,\beta_j}{\text{minimize}} \quad E[(R_{i,t} - \alpha - \beta' R_t')^2] \\ & \text{subject to} \quad \sum \beta = 1 \qquad \beta_j \geq 0 \end{aligned} \tag{10}$$

$$R' = vector\ containing\ excess\ index\ returns$$

$$\beta' = vector\ containing\ corresponding\ factor\ loadings$$

In this framework, the return of a fund is decomposed into style and skill. Style represents the correlation of funds return to pre-defined benchmarks and skill represent security selection. The division of returns in style and skill are important, from an investor perspective, in two ways. First, it acts as a transparent source for evaluating fund managers performance and distinguishes performance between the choice of asset class and prudence in security selection. Second, investors can achieve diversification by allocating investments across preferred styles.

[32] The Elton et al. (1995) does not conform to the required assumptions needed in this framework. As the model uses the difference of indices as factors, restricting the betas would effectively implicate that funds cannot be exposed to the lower risk classes within the market.

Standard Error Correction

Standard errors for all models within the study are calculated by applying Newey & West (1987) correction for serial correlation, following the methodology of Warner & Kothari (2001). An automatic bandwidth section procedure is used following Newey & West (1994). This correction is introduced to correct for heteroscadicity and serial correlation within the returns of the funds. The procedure is done for both sections of the analysis. Mitchell (2009) suggests that both OLS and Fama & MacBeth (1973) standard errors are severely biased, and that the procedure minimized this inefficiency.

Table 3: Summary of Model Structure

Model	Independant Variables/Market Indices included	Risk factor‘s
Single index	S&P Norway Investment Grade Corporate Bond Index	Market
Elton et al. (1995)	S&P Norway Sovereign Bond 7-10 Year Index Index (−) ST1X	Term premium
	S&P Norway Investment Grade Corporate Bond Index (−) S&P Norway Sovereign Bond Index	Credit premium
	Oslo Børs Stock Market Index (OSEBX)	Economic conditions
	S&P Norway Investment Grade Corporate Bond Index	Market exposure
Bessembinder et al. (2009) (Unconstrained and subject to $\sum \beta = 1 \, \beta_j \geq 0$)	S&P Norway 10+ Year Investment Grade Corporate Bond Index S&P Norway 5-10 Year Investment Grade Corporate Bond Index S&P Norway 3-5 Year Investment Grade Corporate Bond Index S&P Norway 0-3 Year Investment Grade Corporate Bond Index	Term premium
	S&P Norway Sovereign Bond Index	Credit premium

This table presents the risk factors used covered within this study. The table lists all the bond market factors employed in the empirical analysis of the Single index and Multi-index models of Elton et al. (1995) and Bessembinder et al. (2009).

4.2 Predicting Bond Fund Performance

We now present the methodology to test the second hypothesis. Our aim is to look at whether mutual fund performance can be predicted by fund specific characteristics. This section closely follows Amihud & Goyenko (2013). We begin by introducing the factors which can have an impact on future fund performance after which we present the technical approach for determining the predictive impact of each factor on fund performance.

4.2.1 Factors

Amihud & Goyenko (2013) (henceforth AG) adopt an approach to test the predictive power of factors on fund performance. Notably, they argue that factors from multi-factor index models (R^2 and alpha) and fund specific characteristics age, expense ratio, management tenure, size and turnover ratio can effect and determine future period performance. We elaborate the underlying theory and the practical importance of the factors.[33]

Age

Age is defined by the start date of a fund. Research on age as a factor influencing performance is scarce, and a handful of studies find mixed results. Otten & Bams (2002) suggest that there is a negative relationship between age and performance whereas Low (2010) find a non-significant effect for this variable. Thus, there is inconclusive evidence whether age can effect performance or not. However, studies have included it as a control variable. (See Chen et al. (2004) and Jiang, Shen, Wermers & Yao (2016)). In line with AG we include age as a control variable.

Alpha - Persistence measure

Alpha is a metric to test the persistence of performance, as it is essentially a one period lagged dependent variable. The alphas are estimated each half year period using the mul-

[33]AG uses the underlying factors in the lagged form.

tifactor models explained in the previous section. The reasoning for adding this factor is to see if the current half-year period's risk-adjusted return can be explained by the previous half-year periods risk-adjusted return. Short-term persistence in returns has been supported by a variety of research papers. Herrmann & Scholz (2013) use Fama & MacBeth (1973) estimators in a study on hybrid mutual funds and find that there is significant persistence in quarterly abnormal returns. Furthermore, Kahn & Rudd (1995) find a significant one-month persistence for fixed income funds. We wish to include alpha to determine whether bond funds exhibit half year persistence in abnormal returns.

Expense ratio

In the performance evaluation section, we looked at the expense ratio by changing the dependent variable from net to gross returns. In this section, we will also include the expense ratio as a factor/independent variable. AG conducted the analysis on net returns. Our focus is to enrich the empirical literature by conducting both the analysis on gross and net returns. By including it as an independent variable, we can determine from an investor point of view, whether expense ratio has an impact on performance. By excluding it with the gross analysis, we can better establish the relationship of other factors, from a fund managers perspective. In this manner, we add robustness, and are able to look at possible differences that might have effected earlier studies.[34] The importance of including this factor is compelling given the current context of the Norwegian mutual fund market i.e. the ongoing law suit on equity mutual funds and the steep inflows in bond funds over the last decade. To the best of our knowledge, we are the first to determine the relationship of expense ratio and bond fund performance in Norway.

TR^2 - Selectivity Measure

AG defines 1-R^2 as a metric to measure the selectivity in mutual funds. The fund's R^2 reflects the proportion of variance in the dependent variable explained by the variation in

[34]Following Fama & French (2010), the gross return could be a better metric for looking at the performance of a fund.

the independent variables. Higher the R^2, closer will be the return variation of funds to the return variation of benchmarks, and vice versa. Selectivity can be defined as the proportion of the funds variation arising due to the idiosyncratic risk or the multi-factor tracking error variance. This can be seen in the equation below:

$$1 - \mathtt{R}^2 = \frac{\mathtt{RMSE}^2}{\mathtt{Variance}} = \frac{\mathtt{RSME}^2}{\mathtt{Systematic\ Risk}^2 + \mathtt{RMSE}^2} \tag{11}$$

where, the volatility of the residual is represented by $\mathtt{RSME}^2$ or Root Mean Squared Error. In equation (11), the variation that can be attributed to the weighted benchmark index is represented by $\mathtt{Systematic\ Risk}^2$. Selectivity is less if the volatility of residuals is lower relative to the total variance of the dependent variable. The paper also highlights that the a low R^2 can be explained by factor loadings that vary over time, implying that one benchmark may not be sufficient over the period of analysis.

The distributional properties of R^2 tend to be negatively skewed, with majority of the values close to one. As a result, AG suggests that adjustments should be made to the R^2. We derive the logistic transformation measure TR^2 as first suggested by Cox (1970). This can be defined by:

$$TR^2 = \mathtt{log}\left(\frac{(\sqrt{\mathtt{R}^2} + \mathtt{c})}{(1 - \sqrt{\mathtt{R}^2} + \mathtt{c})}\right) \tag{12}$$

where, c represents the number of days in the semi-annual measurement period. The estimation of R^2 follows the underlying half year regressions in the analysis. In this way we are able to derive a more symmetric distribution of TR^2. According to our knowledge, this is the first non-U.S. study to use TR^2 on bond mutual funds.

Size

Size is the assets under management, also referred as Total Net Assets (TNA), within each fund. The literature surrounding the effect of size on performance is extensive. Bodson, Cavenaile & Sougné (2011) present a summary of this research in a comprehensive manner, and point out that majority of the studies have found no relationship between size and performance. However, their study on determining the effect of size and performance suggested that there is a quadratic concave relationship.[35] Chen et al. (2004) and Yan (2008) find an inverse relationship between the size and performance as a result of organizational diseconomies and liquidity factors. Incited by the discussion of these studies, we wish to look at the effect of size on the performance of Norwegian Bond Funds. In line with AG, we will use the log size and log size^2 in this study. According to our knowledge, no study has been done on this factor within the mutual fund market in Norway.

Excluded factors

Apart from the factors mentioned above, AG includes style dummies, management tenure and fund turnover. The style dummies included in AG represent differing investment objectives for the sampled funds. Our study focuses on one style, namely the investment grade bond fund market. Accordingly, we include one style dummy which will be notional and have no impact. The management tenure can be defined as the time period for which the manager has managed the fund. Fund turnover is the rate at which the fund managers change the composition of the portfolio. No databases provided information about management tenure for funds and we also tried to gather this by calling companies. However, we were not able to get access to such data. Therefore, the management tenure factor has been excluded. The fund turnover was available for 30% of the period. Hence, we also excluded this factor. AG uses these two factors as control variables and finds persistence to be the only significant predictor of performance in the US bond fund market.

4.2.2 Technical Approach

We now demonstrate the spirit of AG and Fama & MacBeth (1973) used in this study. The aim is to test whether mutual fund performance can be predicted by the before mentioned

[35] A quadratic relationship implies a U-shaped relationship meaning that small and big size funds have a negative relationship and that medium size funds have a positive relationship with the performance of funds.

factors. To do this, we will look at 20 half-year periods from our dataset of ten years, between October 2006 and September 2016. The fundamental relationship we will test is expressed in the equation below:

$$\alpha = \gamma + \gamma \mathtt{TR}^2 + \gamma \mathtt{Alpha} + \gamma \mathtt{log(Size)} + \gamma \mathtt{log(Size)}^2 + \gamma \mathtt{Age} + \gamma \mathtt{Exp} + \epsilon \quad (13)$$

where Alpha and $\mathtt{TR}^2$ are based on three multifactor models i.e. Elton et al. (1995), Bessembinder et al. (2009) and QP Bessembinder et al. (2009) for 20 half year periods for each fund.

Following we present a three-step procedure to estimate the coefficients of each factor (The detailed explanation can be seen in Appendix 2). The first step involves estimating data points for the factors that will be used in the analysis. After that, we run a cross sectional regression at each time period following equation (13). The last step involves calculating the Fama & MacBeth (1973) estimators that represent the factor coefficients.

Step 1: Estimating Variables

The data gathered from external sources in this analysis includes measures for size, age and expense ratio. The remaining variables, α and TR^2, will have to be estimated by time series regressions. The estimation process is done by dividing the sample of 2500 returns into 20 half-year periods. The estimation of each variable involves regressing fund returns within a sequence of daily observations. The pricing model specifications, as introduced in the previous section of the analysis, will function as a tool to estimate the data in this step.[36] We will now explain the process in greater detail.

The estimation procedure involves applying the general regression model in equation (14), where the model specifications/independent variables are represented by ψ. The daily returns

[36]As pointed out in the previous analysis, the introduced pricing models will give different estimates for both alpha and R^2. To add robustness to the results, we will apply the three preferred models in the estimation of the dataset.

within each half year period is represented by each sequence t. By running a regression within each t, we estimate a performance measure for 20 half-year periods for each fund. The time sequences consist of 125 daily returns for 18 funds.

$$\mathtt{R}_{i,t} = \alpha_{i,t} + \psi\beta\mathtt{I} + \epsilon_{i,t} \tag{14}$$

$$\psi = Pricing\ model\ sheme$$

$$i = 1, \ldots, 18$$

$$t = [1:125], [126:250], [251:375], \ldots\ldots\ldots\ldots, [2376:2500]$$

where the ψ, for instance represents the Bessembinder et al. (2009) model. The procedure involves making 360 ($20 * 18$) regressions and collecting alpha (α) and R^2 for each fund. The result of this is a panel data set for each variable. Using daily data enables us to get 20 half year data points for each of the 18 funds, based on a pricing test of 125 data points within each period.[37] From this calculation, we have gathered data for all variables that will be the basis of our analysis.

The variables that have been gathered from external sources are expressed as daily observations. To conform the data frequency to the estimated variables, we calculate the mean of each measure within each half yearly time sequence t. Furthermore, we perform logarithmic transformations to the measure of size and R^2. The transformation of R^2 follow equation (12). In addition, we add a quadratic term of the transformed size variable. These conversions are done in line with AG.

Overall, we have a panel data of all variables introduced in equation (13), which consist of data points for each fund for every half-year period. We will now introduce the cross sectional regression procedure.

[37]Amihud and Goyenko (2013) use a minimum of 120 data points for each half year.

Step 2: Cross sectional estimators

The panel data analysis will follow a procedure introduced by Fama & MacBeth (1973). The method is a frequently applied method within empirical finance, and it has been used in prominent research papers (see Chen et al. (2004)). This procedure enables us to control for cross-sectional correlations when estimating the standard errors. However, the methodology does not control for time-series autocorrelation and heteroscadicity. Therefore, we use the earlier mentioned standard error correction procedure following Newey & West (1994).

In the following procedure, we run the regression as shown in equation (13) at each cross section of the datasets. The Fama & Macbeth (1973) procedure requires estimating the factor betas by running a cross-sectional regressions at each time period t. This implies regressing fund alphas against the factors calculated in the last step to determine factor loadings at each time period t. This step produces $T-1$ factor loadings γ for each variable j. The following equation details the explanation for the estimation procedure:

$$
\begin{aligned}
\alpha_{i,1} &= \gamma_{1,0} + \gamma_{1,F_1}\mathrm{F}^1_{i,1} + \gamma_{1,F_2}\mathrm{F}^2_{i,1} + \gamma_{1,F_3}\mathrm{F}^3_{i,1} + ... + \gamma_{1,F_m}\mathrm{F}^m_{i,1} + \epsilon_{i,1} \\
\alpha_{i,2} &= \gamma_{2,0} + \gamma_{2,F_1}\mathrm{F}^1_{i,1} + \gamma_{2,F_2}\mathrm{F}^2_{i,1} + \gamma_{2,F_3}\mathrm{F}^3_{i,1} + ... + \gamma_{2,F_m}\mathrm{F}^m_{i,2} + \epsilon_{i,2} \\
&\vdots \\
\alpha_{i,T} &= \gamma_{T,0} + \gamma_{T,F_1}\mathrm{F}^1_{i,T} + \gamma_{T,F_2}\mathrm{F}^2_{i,T} + \gamma_{T,F_3}\mathrm{F}^3_{i,T} + ... + \gamma_{T,F_m}\mathrm{F}^m_{i,T} + \epsilon_{i,T}
\end{aligned}
\tag{15}
$$

$$t = 1, ..., T \quad j = 1, ..., m$$

This exercise generated a set of regression coefficients for each time period t. As a result, we have multiple γ's for each factor. In the final step we will estimate a single measure that represents the factor coefficients.

Step 3: Factor Coefficients

Estimated γ's are then used to calculate the Fama & MacBeth (1973) estimators. By assuming ϵ to be i.i.d., coefficient of each factor j can be calculated by taking the mean of γ_j. This results in one estimate $\mathtt{RP}_{\mathtt{F}_\mathtt{j}}$ for every factor.

$$\mathtt{RP}_{\mathtt{F}_\mathtt{j}} = \frac{1}{T}\sum_{t=1}^{T}\gamma_{t,j} \tag{16}$$

$\mathtt{RP}_{\mathtt{F}_\mathtt{j}}$ is the estimate that appears in the table of results (Table 10). In our analysis, we have a total of 20 time periods (represented by T), and five factors (represented by m) within the gross analysis and six factors within the net analysis. The reason being that we omit expense ratio as a factor when running the procedure on gross returns. To generalize the example, we have $t = 1$ in the cross-sectional regressions above. However as we use lagged values we essentially start at $t = 2$, resulting in a total of 19 time periods of analysis for which the mean is taken.

In total we include six models which follow the three steps highlighted above. The only changes across these models are the estimation of data in the first step. We use three different pricing model schemes, and divide the analysis on gross and net returns. This results in different estimations for α and TR^2 only.

5 Empirical Results

5.1 Estimating Bond Fund Performance

This section presents the results for all the selected models used to estimate performance. Our interest is to look at gross and net analysis to investigate the fund performance. Hence, the result tables will have two panels i.e. Panel A for gross return analysis and Panel B for net return analysis. We display coefficients (betas) and alphas for the gross return analysis in Panel A and alphas for the net return analysis in Panel B for all models. Table 4 shows the abbreviations of the funds and indices used with the models.

Table 4: Abbreviations for Funds and Indices

Fund	Code	Index	Code
Alfred Berg Lang Obligasjon	ABL	S&P Norway Investment Grade Corporate Bond Index	*Corp*
Alfred Berg Obligasjon	AB	S&P Norway Sovereign Bond Index	*Sov*
Carnegie Obligasjon	Car	S&P Norway AAA Investment Grade Corporate Bond Index	AAA
Danske Invest Norsk Obligasjon	Danske	S&P Norway AA Investment Grade Corporate Bond Index	AA
DNB Kredittobligasjon	DNBK	S&P Norway A Investment Grade Corporate Bond Index	A
DNB Lang Obligasjon 20	DNBL20	S&P Norway BBB Investment Grade Corporate Bond Index	BBB
DNB Obligasjon III	DNBIII	S&P Norway 10 + Year Investment Grade Corporate Bond Index	10+
DNB Obligasjon 20 I	DNB20I	S&P Norway 5-10 Year Investment Grade Corporate Bond Index	5-10
DNB Obligasjon 20 II	DNB20II	S&P Norway 3-5 Year Investment Grade Corporate Bond Index	3-5
DNB Obligasjon 20 III	DNB20III	S&P Norway 0-3 Year Investment Grade Corporate Bond Index	0-3
DNB Obligasjon 20 IV	DNB20IV	Oslo Børs Government Bond Index 0.25 Year	ST1X
Handelsbanken Obligasjon	Handel	S&P Norway Sovereign Bond 1-5 Year Index	Sov_{1-5}
KLP Obligasjon 3 AR	KLP3	S&P Norway Sovereign Bond 5-10 Year Index	Sov_{5-10}
KLP Obligasjon 5 AR	KLP5	S&P Norway Sovereign Bond 7-10 Year Index	Sov_{7-10}
Nordea Obligasjon II	NordII	Oslo Børs Stock Benchmark Index	*Stock*
Nordea Obligasjon III	NordIII		
Pareto Obligasjon	Par		

This table shows the abbreviated code for each fund and index. The fund and index code will be used throughout the analysis. The use of abbreviated codes is adopted so as to structure the results of each model for easier comparison of gross and net analysis.

5.1.1 Single Index Model

In this model, we regress the excess returns of each fund on the excess returns of the Norwegian Corporate Bond Index. Table 9 shows the results of this analysis. All funds show a significant loading on/exposure to the index. In Panel A, we see that 11 funds have a significant positive alpha gross of expenses. However, most of the funds only have a low level of significance. Overall, the model is able to explain between 41.72 - 77.26% of the variation in returns, represented by the R^2.

In Panel B we see that there is a drop in the number of significant alphas. There are only five funds with a significant alpha. Specifically, we see that DNB Kredittobligasjon and DNB Obligasjon 20 I stand out with a net alpha of above one percent with a strong significance. At the other end, Pareto Obligasjon and Handelsbanken Obligasjon are the only funds with an insignificant negative alpha.

As highlighted in the methodology, a single index model can be naive in estimating abnormal performance. It does not reveal the differences within the investment style of individual funds. For instance, a fund that has a higher exposure to long duration bonds would have a higher risk and expected return than a fund that has a higher exposure to short duration bonds. Thus, a multifactor model offers estimation based on loadings on the sub-indices within the market representing the theoretical risk and return differences (Fama & French (1993).

Table 5: Single Index Model

Panel A, Gross return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.9653*	1.0169*	0.6409	0.9525*	1.2837***	0.2815	1.4887***	1.3044***	0.8551*
	(0.4025)	(0.4200)	(0.3836)	(0.4331)	(0.3069)	(0.4563)	(0.2838)	(0.2844)	(0.3566)
Corp	1.3051***	0.7385***	0.8208***	0.8152***	0.7364***	1.3014***	0.7192***	0.7227***	0.7737***
	(0.0337)	(0.0207)	(0.0226)	(0.0216)	(0.0238)	(0.0358)	(0.0235)	(0.0236)	(0.0226)
R^2	.7217	.5935	.5526	.6272	.6244	.7072	.6071	.6075	.6520

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.8497*	0.8488*	0.8540*	−0.2785	0.3461	0.2596	0.4838	0.7316**	0.2392
	(0.3518)	(0.3517)	(0.3531)	(0.4731)	(0.2741)	(0.3346)	(0.2802)	(0.2496)	(0.2632)
Corp	0.7738***	0.7741***	0.7774***	1.5136***	0.7961***	1.4336***	0.8299***	0.8147***	0.5274***
	(0.0224)	(0.0224)	(0.0225)	(0.0427)	(0.0218)	(0.0433)	(0.0226)	(0.0226)	(0.0276)
R^2	.6524	.6525	.6527	.7183	.6946	.7736	.6800	.6831	.4172

Panel B, Net return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.3653	0.4169	0.2909	0.4525	1.0837***	0.2815	0.6887*	1.1044***	0.3551

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.4997	0.6488	0.7040*	−0.7285	0.1461	0.0596	0.2838	0.5813*	−0.2605

This table shows the results for the single index model. The factor used within the model is the S&P Corporate Bond Index. Panel A presents the results for gross analysis showing the estimated betas and alpha for each fund. Panel B presents the results for net analysis showing the estimated alpha for each fund.

5.1.2 Elton et al. (1995) Model

The multifactor model introduced by Elton et al. (1995), considers a funds exposure to the Stock market, the bond market, the credit premium and the term premium in estimating the risk-adjusted measure of performance. Table 8 shows the results from the Elton et al. (1995) model. In Panel A, we see that all the funds have a high significant exposure on the corporate bond index. This finding indicates that the corporate bond index is able to explain most of the variation in returns as compared to other factors. Furthermore, the exposure to the corporate bond index is reasonable as the index represents 69% of the Norwegian bond market (Stamdata). Across the sample, there is marginal or close to zero loading on the stock market index. For the term premium, most of the funds have negative loading with low significance. This implies that the funds tend to have higher exposure to bonds with lower term risk within the proxied range of which the factor is built. Further, all funds have a significantly negative loading on the credit premium. The model is able to explain between 47 - 85% of the variation in fund returns.

Panel A shows that all funds have a positive alpha, with 14 funds having statistical significance. This indicates that funds can earn an abnormal return before fees. Panel B shows that there is a substantial decline in the number of significant alphas whereby we observe only six funds to have a positive significant alpha. Similar to the single index model, there are two funds which have a negative non-significant alpha. This indicates that fees has a negative impact on most funds ability to generate abnormal returns for the investors. However, two funds (DNBK and DNBIII) show the ability to generate positive returns to investors up to 1.2%, net of fees with a strong significance.

We find that the additional factors are able to capture the return differences for most of the funds better. It seems to be particularly superior for funds that have a significant exposure to the credit premium and the stock market index.

Table 6: Elton et al. (1995) Model

Panel A, Gross return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	1.1155**	1.1021*	0.8008*	1.0704**	1.4039***	0.4898	1.6385***	1.4555***	0.9866*
	(0.4296)	(0.4667)	(0.3782)	(0.3695)	(0.2854)	(0.5515)	(0.3965)	(0.3930)	(0.3910)
Stock	−0.0001	0.0011	−0.0013	−0.0019	−0.0019	−0.0021	−0.0017	−0.0017	−0.0016
	(0.0026)	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0028)	(0.0018)	(0.0018)	(0.0015)
Corp	1.2185***	0.8044***	0.9369***	0.8383***	0.7422***	1.2559***	0.7602***	0.7661***	0.8021***
	(0.0558)	(0.0541)	(0.0489)	(0.0416)	(0.0418)	(0.0619)	(0.0429)	(0.0429)	(0.0415)
Term	0.0204	−0.0442*	−0.0805***	−0.0291	−0.0211	−0.0088	−0.0425*	−0.0438*	−0.0336*
	(0.0284)	(0.0219)	(0.0238)	(0.0174)	(0.0197)	(0.0266)	(0.0183)	(0.0183)	(0.0150)
Credit	−0.1436*	−0.1402***	−0.2078***	−0.1171**	−0.1127*	−0.1954**	−0.1635***	−0.1661***	−0.1383***
	(0.0651)	(0.0382)	(0.0571)	(0.0442)	(0.0452)	(0.0632)	(0.0410)	(0.0412)	(0.0362)
R^2	0.7394	0.6007	0.5621	0.6338	0.6342	0.7250	0.6213	0.6218	0.6623

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.9811*	0.9807*	0.9865*	0.1852	0.5577	0.6778*	0.6855*	0.8877*	0.4906
	(0.3909)	(0.3908)	(0.3924)	(0.3370)	(0.2905)	(0.2844)	(0.3165)	(0.3479)	(0.2942)
Stock	−0.0016	−0.0016	−0.0016	−0.0054***	−0.0016	−0.0047**	−0.0019	−0.0007	−0.0016
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0014)	(0.0017)	(0.0017)	(0.0017)	(0.0011)
Corp	0.8032***	0.8041***	0.8078***	1.2378***	0.8041***	1.2659***	0.8754***	0.8586***	0.6337***
	(0.0415)	(0.0414)	(0.0415)	(0.0656)	(0.0343)	(0.0552)	(0.0359)	(0.0379)	(0.0503)
Term	−0.0341*	−0.0345*	−0.0347*	0.0654*	−0.0353**	0.0194	−0.0522***	−0.0444**	−0.0891***
	(0.0150)	(0.0150)	(0.0151)	(0.0317)	(0.0110)	(0.0234)	(0.0127)	(0.0147)	(0.0171)
Credit	−0.1389***	−0.1396***	−0.1404***	−0.3627***	−0.2249***	−0.3586***	−0.2226***	−0.1870***	−0.3072***
	(0.0363)	(0.0363)	(0.0365)	(0.0790)	(0.0308)	(0.0600)	(0.0338)	(0.0371)	(0.0445)
R^2	0.6627	0.6628	0.6630	0.8152	0.7332	0.8508	0.7043	0.7001	0.4706

Panel B, Net return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.5155	0.5021	0.4508	0.5704	1.2039***	0.4898	0.8385*	1.2555**	0.4866

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.6311	0.7807*	0.8365*	−0.2648	0.3577	0.4778	0.4855	0.7374*	−0.0091

The table presents the results for the Elton et al. (1995) model. This model is used to estimate the exposures of each fund to four factors. These include the Oslo Børs Stock Market Index (*Stock*), S&P Norway Investment Grade Corporate Bond Index (*Bond*), Term premium and Credit premium. *Term* is the difference between S&P Sovereign Bond 7-10 Year Index and Oslo Børs Government Bond Index 0.25 Year Index. *Credit* is the difference between the S&P Corporate Bond Index and the S&P Norway Sovereign Bond Index. Panel A presents the results for gross analysis showing the estimated betas and alpha for each fund. Panel B presents the results for net analysis showing the estimated alpha for each fund.

5.1.3 Bessembinder et al. (2009) Model

This model aims to capture the term and risk premium by including four indices with different maturities and the Sovereign bond index. Table 7 presents the results for the for the Bessembinder et al. (2009) model. All funds show a significant positive loadings on the Sovereign, 3-5 and 5-10 (maturity) indices. Predominantly the loadings for all funds are higher on the 3-5 and 5-10 maturity indices. However, exception to this is the Handels fund, which has a greater exposure, though marginally, to the sovereign index. Further, there is significant positive loading on factor 0-3 for 12 funds and factor 10+ for five funds. However, Par fund shows a significant negative loading on the 10+ index. We see a general tendency that funds are not exposed to the bond index with more than ten years to maturity, which can be explained by the low insignificant estimates for most of the funds. The explanatory variable seems to be the highest among all the models presented so far, which is between 48 - 86%.

In Panel A, we see that 12 funds indicate a significant positive alpha. Compared to the Elton et al. (1995) model, there are two less significant number of alphas.[38] In Panel B, we observe only five funds to have a significant positive alpha. Consistent with our findings within previous models, there is a sharp decline in a number of significant alphas, and two funds show a non-significant negative alpha. Therefore, our results indicate that funds seem to utilize selection and timing ability to produce abnormal returns. However, this implication is strongly visible for two funds, DNBK and DNB III, which seem to produce abnormal returns that exceed the impact of expenses, with a strong significance level.

Compared to the Elton et al. (1995) model, the risk-adjusted return estimates and the significance levels are lower within this model. Further, the model seems to be marginally better at explaining the variations in individual bond returns due to an additional variable. This also explains the increase in the explanatory variable. Bessembinder et al. (2009) in their study concluded that this model produced less biased results as compared to the Elton et al. (1995) model which tends to have upward biased results. Following we argue that the results presented in the model are more realistic.

[38]The two funds which don't have significant positive alphas vis-a-vis Elton et al. (1995) model are Car and Nord II.

Table 7: Bessembinder et al. (2009) Model

Panel A, Gross return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	1.0810*	0.9710*	0.5652	0.9127*	1.3124***	0.3889	1.5160***	1.3309***	0.8490**
	(0.4294)	(0.3955)	(0.3650)	(0.4346)	(0.3207)	(0.4204)	(0.3038)	(0.2983)	(0.3182)
Sov.	0.1496***	0.0525**	0.0787*	0.0629**	0.0686**	0.1487***	0.0781**	0.0786**	0.0670**
	(0.0354)	(0.0201)	(0.0326)	(0.0243)	(0.0222)	(0.0380)	(0.0263)	(0.0272)	(0.0234)
10y+	0.0540*	−0.0002	−0.0201	0.0049	0.0224*	0.0430*	0.0170	0.0171	0.0107
	(0.0221)	(0.0144)	(0.0108)	(0.0123)	(0.0102)	(0.0204)	(0.0102)	(0.0101)	(0.0115)
5-10y	0.1845***	0.1311**	0.1223***	0.1173***	0.1075***	0.1898***	0.1033***	0.1036**	0.1129***
	(0.0513)	(0.0425)	(0.0371)	(0.0349)	(0.0302)	(0.0513)	(0.0307)	(0.0322)	(0.0318)
3-5y	0.3790***	0.2290***	0.2792***	0.2843***	0.2137***	0.4220***	0.2228***	0.2206***	0.2802***
	(0.0660)	(0.0483)	(0.0564)	(0.0476)	(0.0431)	(0.0664)	(0.0410)	(0.0418)	(0.0445)
0-3y	0.3759*	0.3738**	0.5160**	0.3933*	0.2966*	0.2970	0.2650*	0.2751*	0.2714
	(0.1773)	(0.1390)	(0.1778)	(0.1700)	(0.1322)	(0.2034)	(0.1347)	(0.1386)	(0.1389)
R^2	0.7475	0.6098	0.5625	0.6382	0.6332	0.7324	0.6228	0.6231	0.6681

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.8430**	0.8418**	0.8471**	0.1714	0.4086	0.5910*	0.4914	0.7241*	0.2557
	(0.3130)	(0.3180)	(0.3194)	(0.3378)	(0.2627)	(0.2768)	(0.2842)	(0.3306)	(0.2610)
Sov.	0.0668**	0.0670**	0.0674**	0.4497***	0.1622***	0.3590***	0.1174***	0.0965***	0.1553***
	(0.0237)	(0.0235)	(0.0236)	(0.0466)	(0.0257)	(0.0410)	(0.0220)	(0.0237)	(0.0323)
10y+	0.0107	0.0107	0.0108	0.0560**	0.0117	0.0453**	0.0063	0.0108	−0.0251*
	(0.0114)	(0.0114)	(0.0115)	(0.0187)	(0.0082)	(0.0160)	(0.0093)	(0.0100)	(0.0106)
5-10y	0.1129***	0.1128***	0.1133***	0.1210***	0.0643*	0.1329**	0.0920**	0.0953**	0.0239
	(0.0318)	(0.0318)	(0.0320)	(0.0353)	(0.0299)	(0.0414)	(0.0325)	(0.0339)	(0.0273)
3-5y	0.2794***	0.2785***	0.2789***	0.4427***	0.2437***	0.4772***	0.3147***	0.2920***	0.2301***
	(0.0446)	(0.0446)	(0.0448)	(0.0841)	(0.0452)	(0.0643)	(0.0461)	(0.0472)	(0.0430)
0-3y	0.2743*	0.2775*	0.2803*	0.0375	0.3626**	0.0577	0.2985*	0.3432*	0.2249
	(0.1398)	(0.1394)	(0.1401)	(0.1345)	(0.1381)	(0.1452)	(0.1482)	(0.1576)	(0.1264)
R^2	0.6685	0.6686	0.6687	0.8168	0.7385	0.8575	0.7159	0.7119	0.4805

Panel B, Net return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.4810	0.3710	0.2152	0.4127	1.1124***	0.3889	0.7160*	1.1309***	0.3490

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.4930	0.6418*	0.6971*	−0.2786	0.2086	0.3910	0.2914	0.5738	−0.2440

The table presents the results from Bessembinder et al. (2009) model. The model is used to estimate the exposures of each fund to the five benchmarks. These include the Norwegian Sovereign Bond Index and four S&P Corporate Bond Index with $0-3$, $3-5$, $5-10$ and 10+ year maturity. Panel A presents the results for gross analysis showing the estimated betas and alpha for each fund. Panel B presents the results for net analysis showing the estimated alpha for each fund.)

5.1.4 Quadratic Programming Bessembinder et al. (2009) Model

We now present the results from the restricted form of the Bessembinder et al. (2009) model which we define as Quadratic Programming Bessembinder et al. (2009). Table 8 shows the results from this model. A majority of the funds have exposure greater than 50% on corporate bonds with a maturity of 0-3 years. However, we see that some funds tend to be exposed to only a specific maturity range. For instance, Handel and KLP 5 fund do not have any exposure to corporate bonds with a maturity of 0-3 years. On the contrary, Par fund is primarily exposed to short-term bonds while having a 77% factor loading on corporate bonds with a maturity of 0-3 years. As expected, the coefficient of determination decreases marginally when we apply the restrictions.

We find that the estimates of risk-adjusted return and their significance levels are similar to those in the Bessembinder et al. (2009) model. The results are consistent in both net and gross returns, with 72% of the funds experiencing a slight decrease in risk-adjusted return. The differences in the estimates risk-adjusted return, and significance levels are marginal.[39] The magnitude of the differences is approximately 0.15 percentage point on average. An interesting point is that the funds with the largest alpha estimates in the unrestricted model experience the largest decrease, which would decrease their significance level.

The quadratic programming model has explanatory variable between 44 - 86%, which is lower than the unrestricted model. However, the applicability of this model has to be seen in context with the theoretical efficiency gains, as highlighted by Kahn & Rudd (1995). Therefore, it is difficult to evaluate these models fit as compared to the other models. We use this model as a comparative model to add robustness to our analysis.

[39] As a result of the quadratic programming scheme, we do not produce standard errors. However, the significance of these variables will be compared with the unrestricted model.

Table 8: Quadratic Programming Bessembinder et al. (2009) Model

Panel A, Gross return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	1.1455	0.8767	0.5690	0.8509	1.1812	0.4342	1.3745	1.1936	0.7328
Sov.	0.1435	0.0609	0.0752	0.0686	0.0809	0.1444	0.0913	0.0915	0.0778
10y+	0.0557	0	0	0.0033	0.0190	0.0442	0.0132	0.0135	0.0076
5-10y	0.1886	0.1219	0.0992	0.1134	0.0992	0.1927	0.0944	0.0950	0.1056
3-5y	0.4197	0.1668	0.2611	0.2453	0.1311	0.4506	0.1336	0.1340	0.2069
0-3y	0.1924	0.6504	0.5645	0.5694	0.6699	0.1681	0.6675	0.6660	0.6020
R^2	0.7463	0.6029	0.5612	0.6357	0.6197	0.7318	0.6068	0.6082	0.6581

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.7277	0.7276	0.7348	0.3218	0.3386	0.6593	0.4143	0.6511	0.0912
Sov.	0.0776	0.0777	0.0779	0.4372	0.1687	0.3531	0.1246	0.1033	0.1586
10y+	0.0077	0.0077	0.0078	0.0713	0.0099	0.0511	0.0043	0.0089	0
5-10y	0.1056	0.1056	0.1062	0.1343	0.0599	0.1386	0.0872	0.0907	0
3-5y	0.2068	0.2065	0.2081	0.3573	0.1995	0.4572	0.2662	0.2460	0.0764
0-3y	0.6023	0.6025	0.5999	0	0.5620	0	0.5178	0.5512	0.7650
R^2	0.6587	0.6589	0.6594	0.8147	0.7348	0.8570	0.7119	0.7082	0.4435

Panel B, Net return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.5455	0.2767	0.2190	0.3509	0.9812	0.4342	0.5745	0.9936	0.2328

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.5701	0.7201	0.7778	-0.0279	0.3053	0.6593	0.3977	0.6843	-0.3171

The table presents the results from the Quadratic Programming of Sharpe (1992) applied on the Bessembinder et al. (2009) model. The technique is used to estimate the exposures of each fund to the five benchmarks. These include the Norwegian Sovereign Bond Index and four S&P Corporate Bond Index with $0-3$, $3-5$, $5-10$ and 10+ year maturity. The estimated betas for each fund sum to one. Panel A presents the results for gross analysis showing the betas and alpha. Panel B presents the results for net analysis showing the estimated alpha.

5.2 Predicting Bond Fund Performance

The basis of this analysis is to test if fund specific characteristics are able to predict abnormal returns. To enable this analysis we first estimate factors that will be used as the dependent variable i.e. the factor reflecting persistence and the factor reflecting selectivity, as they are not gathered from a database. This involves going through step one of the procedure stated in subsection 4.2.2.

By using the exact regression specifications from the asset pricing section, we gather α and R^2 for a total of 20*18 regressions per model. We regress each fund return in a rolling window of 125 days (for a total of 18 funds over 20 half years). A summary of these results is gathered in Table 9, where TR^2 is the logarithmic transformation of R^2.[40]

Based on half yearly regressions, we find the different models produce somewhat varying abnormal returns, with the Elton et al. (1995) model producing the highest mean. As indicated in Bessembinder et al. (2009), this model tends to have an upward bias, and same can be seen in Table 9. We also see that the standard deviations can be considered to be very high for the estimations, i.e. the risk-adjusted return based on half yearly tests vary.[41]

After this procedure is done, we have gathered all data for the analysis. This panel data set comprises of data points for all variables for 20 half year periods for the 18 funds. The Fama & MacBeth (1973) procedure is applied to analyze the relationship between equation (15) and (16). Table 10 shows the results of the estimators from the Fama & MacBeth (1973) procedure.

First of all, the estimators for the coefficients of each variable seem to be relatively consistent throughout the underlying models, as well as the use of the net and gross returns. Furthermore, the models can explain 45.32-57.24% of the variations in the risk-adjusted return/alpha of a fund. Also, they are able to explain approximately ten percentage points

[40] Appendix 2 includes an example of full results from step 1 and 2 of the procedure. As a result of the magnitude of data for all model specifications for net and gross returns, we have only included one model specification for net returns Bessembinder et al. (2009) model.

[41] A closer inspection of the data reveals that the variations are considerably higher during the financial crisis.

Table 9: Summary Statistics for Alpha and TR^2 Estimates

	Gross				*Net*			
	Alpha		*TR^2*		*Alpha*		*TR^2*	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Bessembinder et al. (2009) Model	0.73	3.03	1.87	0.37	0.39	5.69	1.87	0.37
Bessembinder et al. (2009) QP Model	0.69	3.21	1.71	0.58	0.35	6.36	1.71	0.58
Elton et al. (1995) Model	0.95	2.46	1.79	0.39	0.61	3.82	1.79	0.39

The table displays descriptive statistics of the estimated alpha and TR^2 in step two. The estimation involves regressing fund returns in the intervals of half year periods. TR^2 is the logistic transformation of R^2 and Alpha is the intercept from the regressions. The procedure follows equation (14). The gathered alpha and TR^2 are used for the predictive analysis as shown in equation (13). The table displays estimates for three model specifications based on the use of gross and net returns. Model specifications ψ include: Elton et al. (1995) model, Bessembinder et al. (2009) model, and the quadratic programming Bessembinder et al. (2009) model.

more of net returns. Also, all variables seem to be relatively consistent with Amihud & Goyenko's (2013) study of the US bond fund market from 2001-2010.

The Alpha represents the last half years risk-adjusted return of a fund and function as a proxy for short-term persistence. The estimate is significant for all models, gross of expenses. The estimates indicate that a positive daily alpha of one percentage point in the previous half year period will lead to an approximate increase in the current risk-adjusted return of 0.3-0.4 percentage points (annualized). This result is also economically significant. In the analysis of net returns the estimates and significance decrease marginally. The only estimate that is insignificant is from the quadratic programming model, net of expenses. The result is consistent with Amihud & Goyenko (2013).[42]

TR^2 acts as a proxy for the level of active bond selection of the funds. The estimates are negative, implying an inverse relationship with R^2 and risk-adjusted return of a fund. Hence, we would expect active bond pickers to generate a higher gross return. However, this result is only slightly significant by applying the Elton et al. (1995) model with net returns. In our model we see, although insignificant, that estimates of a lower R^2 will predict a higher abnormal return. This estimate leads us to believe that an increase in TR^2 of one will lead to a 0.5 decrease in abnormal returns. In general, the significance is not robust, and by applying

[42]The the paper has a considerably larger sample size of funds in a ten year period.

Table 10: Predictive Power of Fund Characteristics, Fama & MacBeth (1973) Regression Results

	Dependent variable: Alpha					
	Gross			Net		
Lagged	(1) Bessembinder et al. (2009) Model	(2) Bessembinder et al. (2009) QP Model	(3) Elton et al. (1995) Model	(4) Bessembinder et al. (2009) Model	(5) Bessembinder et al. (2009) QP Model	(6) Elton et al. (1995) Model
$\texttt{TR}^2_{t-1}$	−0.4903	−0.2393	−0.4479	−0.4876	−0.2591	−0.5133*
	(0.3097)	(0.1855)	(0.2158)	(0.3135)	(0.1976)	(0.2246)
$\texttt{Alpha}_{t-1}$	0.4187**	0.3473*	0.3273**	0.3394*	0.2555	0.2267*
	(0.1431)	(0.1319)	(0.1069)	(0.1512)	(0.1516)	(0.1112)
$\log(\texttt{Size}_{t-1})$	−0.7651	−1.2229	−0.4776	−0.9113	−1.3582	−0.6907
	(0.9822)	(0.6391)	(0.9997)	(1.0263)	(0.8866)	(1.2127)
$\log(\texttt{Size}_{t-1})^2$	0.0196	0.0302	0.0126	0.0234	0.0335	0.0176
	(0.0236)	(0.0173)	(0.0241)	(0.0255)	(0.0222)	(0.0285)
$\texttt{Age}_{t-1}$	0.0096	0.0082	0.0105*	0.0038	0.0046	0.0074
	(0.0052)	(0.0061)	(0.0047)	(0.0048)	(0.0077)	(0.0068)
$\texttt{Expenses}_{t-1}$				−0.3698	−0.6368	−0.7492
				(0.4604)	(0.5204)	(0.5846)
Constant	8.8398	13.1189	6.0712	10.2293	14.5284	8.4902
	(9.0537)	(9.6639)	(9.5179)	(9.3239)	(9.4604)	(11.7226)
Observations	342	342	342	342	342	342
R^2	0.4532	0.4719	0.4652	0.5543	0.5450	0.5724
Note:						*p<0.1; **p<0.05; ***p<0.01

The table displays the results of the Fama & MacBeth (1973) estimators. The estimates represent the risk premium of each factor for Norwegian investment grade bond funds in 2006-2016. Twenty semiannual tests are done to determine the dependent variable, $\alpha_{j,t}$. We obtain estimates for the $R^2_{j,t-1}$, $\alpha_{j,t}$ from the proceeding semiannual test. Funds included have at least 90% of their assets invested in bonds. The underlying models employ daily returns net or gross of expenses. The pricing models used for estimation of variables include the Elton et al. (1995) model and Bessembinder et al. (2009) model. Also, a quadratic programming scheme is used to control for investment style of mutual funds in model (2) and (5), based on the Bessembinder et al. (2009) model.

a quadratic programming scheme, the estimate seems to fall by approximately 50%. The results from are consistent with the study of the US bond fund market by Amihud & Goyenko (2013), in regards to significance.[43]

For the size variables, we find a negative linearly and positive quadratic relationship.

[43]However, in evaluating equity funds their study finds a significant results for this factor.

Building on this we would expect there to be an optimal size to maximize the abnormal return of a fund. From the quadratic term we would have a concave relationship between performances. The estimate is similar to Bodson et al. (2011). However, this result is not close to being significant in either gross or net returns, with standard errors that exceed the estimate in all models except for the quadratic programming model. The insignificant relationship is supported by a number of studies. Elton, Gruber & Blake (2012) suggest that mutual fund size is not as important as earlier studies have found.

The estimates of fund age as a contributing factor to abnormal return display a positive relationship. For gross returns, the estimate is slightly significant when applying the Elton et al. (1995) model. Furthermore, the economic significance seems to be weak as the models the estimate with the highest indicates that a 10-year increase in age of a fund would predict a annualized increase of 0.1% abnormal return. This supports the ambiguity a funds age effect on performance found in literature.

The expense ratio is only included in the model that uses net returns. The results for the expense ration are statistically insignificant. The estimates indicate an inverse relationship, with a one percentage point increase in yearly expense ratio leading to an increase in abnormal return of between 0.4 and 0.7 percentage points. This has to be seen in relation to what the expense ratio currently is for the sampled funds. From Table 1, we see that the general expense ratio is between 0.15-0.7%. As a result, the economic significance of this result is also weak, based on the range of expenses that these funds operate within. Both estimates and insignificance are supported by Amihud & Goyenko (2013).

The constant in this model needs to be looked at with precaution, as it could indicate the risk-adjusted return of a fund if all variables are equal to zero, which is not relevant in this scenario. Also, the result of the constant is not significantly different from zero.

Overall, the results indicate short-term persistence in risk-adjusted returns, while all other factors have a statistically insignificant relationship with the performance measure. Therefore, the only factor that has a predictive power is the last half years alpha.

5.3 Discussion

In evaluating abnormal fund performance, we see that funds that experience the greatest increase in explanatory power (i.e. going from single index model to multi-factor models) are associated with clearer investment profiles when the market is divided across different risk classes. The term and credit risk classes, represented by the indices included in this analysis, explain a good portion of the variation in returns. This underlines the importance of having a model that is able to capture these differences in risk by including the right benchmarks, as stated by Dopfel (2004).

The Elton et al. (1995) model, on average, estimates the highest values of risk-adjusted return, while the restricted Bessembinder et al. (2009) model estimates the lowest. Based on the similarities of the models, it is difficult to conclude which produce the most efficient results. However, in their study concentrating on the accuracy of different models, Bessembinder et al. (2009) highlighted that the Elton et al. (1995) model produced upward biased results. We also included a credit rating based model, similar to the Bessembinder et al. (2009) model.[44] The model divides the corporate bond market within different credit rating classes instead of maturity. It includes more variables which divide the sovereign bond market into different maturity classes to add a term premium proxy. However, the results of the Credit Rating model proved to be inferior to the maturity based model as the explanatory variables were approximately 1-4 percentage points lower. The results for this model can be seen in Appendix 3.

As we have focused on each fund within this study, we find some funds showing the ability to generate risk-adjusted returns exceeding the impact of fees. Especially considering the possibility of a slight upward bias in the analysis, we wish to highlight these funds that can do this with a strong significance across model specifications. The two funds are DNB Obligasjon 20 III and DNB Kredittobligasjon. Furthermore, the estimates indicate that these funds have been able to generate a 0.98-1.3% annualized risk-adjusted return net of expenses.

[44]Bessembinder et al. (2009) found the bias in this model by the use of monthly data frequency.

Overall, the study estimates that a majority of the funds, 67-78% , are able to generate an abnormal return gross of expenses. Since we focus on a small market we are able to look at each fund individually, where most international studies group funds and look at an average return. Recent studies within the US market suggest that funds are on average able to outperform the market gross of expenses, implying that our results are in line with Chen et al. (2010). After deducting expenses taken directly out of the fund, similarly to using the NAV's directly, our results indicate that about 28-33% of the funds remain with a significant positive abnormal return. In the comparison with gross returns, we can infer that the fees seem to deteriorate an average significant abnormal return. This conclusion is in line with the recent study of Moneta (2015) focusing on the impact that fees have on performance.

Considering the possibility of foreseeing abnormal returns, we find persistence to be the only significant predictor of performance. Our study enriches the AG methodology by including the theoretically reasoned strong form of style analysis. In addition, we have also looked at the gross return of the funds. Although the significance level varies to some extent, the estimates are largely robust throughout the different model specifications. The mean explanatory variable of the models is in the range of 45-57%. For the other variables, there are mixed results from related literature of their impact on returns. This is also evident in our study, as none seem to be significantly different from zero. Although with little sign of significance, abnormal fund performance has a negative relationship R^2 and expenses and positive relationship with age and size up to a certain point.

6 Limitations and Future research

In international literature, there is an understanding that funds in general either underperform or have an insignificant abnormal return. Our findings within the Norwegian market indicate a minority of the funds showing a significant positive risk-adjusted return. The results seem to be in the higher range of related findings. Certain aspects might contribute to the higher estimates, which will be further explored in this section.

Survivorship bias

Survivorship bias occurs when the funds exit the market and/ or merge with other operational funds, are not included in the analysis. US research on the topic mostly uses the bias-free Lehman Brothers dataset as the primary source for collecting NAVs. In our dataset, we only include funds that have been active during the time window as survivorship bias-free data is not yet available in Norwegian bond fund market. This is a concern for the analysis as it could have an upward bias in the results as low or poor performing funds tend to close down. However, this bias has a low degree of influence within the bond market as Elton et al. (1993) states that "Survivorship bias is less important for bond funds than it is for equity funds since bond fund performance is less variable and, consequently, fewer funds merge or dissolve".

Defined Investment Universe

Based on the results of our analysis, we checked the underlying documentation of the funds to some extent. Mainly, this was on the basis of varying explanatory power across funds. From this we found that the funds have a varying degree of freedom when it comes to investment possibilities. Especially the DNB funds have a common characteristic of having the ability to invest more within the EU, although their classification from Morningstar suggests a purer investment grade strategy within Norway. Without a clear classification of their holdings available, we are unable to see where they invest and which additional factors we could include. However, since we restricted the minimum requirement in investment grade bonds to 90% this should not have an impact on the results of our analysis.

Further Analysis

The analysis presented in this study uses a return based approach and the indices available in the Norwegian bond mutual market. However, as data about portfolio holdings of mutual funds becomes available, which currently is not, further factors like liquidity can be analyzed. Also, one can test other models by adding factors that have a theoretical reasoning to the bond market. However, to our knowledge, we have included all relevant benchmarks available until end of 2016. Analyzing the holdings of funds might reveal exposures to relevant markets that should be included. Therefore, it would also enrich the research to find other relevant indices to include in the analysis. However, currently the data is sparsely available across the bond market and one should keep in mind the limitations stated within this study while using holding based approach. In addition, including factors representing liquidity could enrich the study for this specific market.

7 Conclusion

In this study, we have compared widely used models and methodologies for estimating the abnormal return of bond portfolios, with a focus on the Norwegian bonds fund market. Also, we have explored the predictive power of a selection of fund characteristics. For both parts of the analysis, a variety of model specifications have been used to assess the robustness of the results.

The performance estimations results indicate that 67-78% of the funds are able to generate significant abnormal returns, gross of expenses. This indicates that most funds can use selection and/or timing ability to beat a relevant benchmark. Further, we find the magnitude of abnormal return to be 1 % before deducting expenses. The results are in line with Moneta (2015). After deducting expenses, our results indicate that about 28-33% of the funds remain with a significant positive abnormal return. This suggests that most funds do not seem to transfer abnormal return across to the investors. The preferred models are able to explain 50-86% of the variations in individual fund returns which is based on the comparison of three multi-factor models.

The ability to predict performance seems to be most clearly defined by a funds ability to produce an abnormal performance in the previous period, which is evidence of one-period persistence in abnormal returns. All other factors are insignificant. The result is in line with Amihud & Goyenko (2013). The estimates indicate that about a third of the risk-adjusted return is carried over to the next period. Thus, the risk-adjusted return can be used as a predictor of performance in the Norwegian bond fund market.

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9 Appendices

Appendix 1

Correlations of Factors Returns

A summary of factor correlations within each model can be seen in tables 10. The general idea is to get an overview of possible multicollinearity within the models. Occurrences of multicollinearity might lead to incorrect inference tests, as highly correlated variables have the ability to affect each other. Our methodology seeks to fulfill some requirements based on related literature, and therefore we do not exclude any of the indices used below on the basis of multicollinearity. Another important part of this is that we aim to replicate widely used models concentrating on bond portfolio performance in international literature.

Bessembinder et al. (2009) Model

	Sov.	10y+	5-10y	3-5y	0-3y
Sov.	1				
10y+	0.69	1			
5-10y	0.73	0.84	1		
3-5y	0.74	0.75	0.83	1	
0-3y	0.56	0.57	0.66	0.81	1

Elton et al. (1995) Model

	Stock	*Bond*	*Term*	*Credit*
Stock	1			
Corp	-0.34	1		
Term	-0.29	0.71	1	
Credit	0.15	-0.24	-0.79	1

Table 11: Correlations of Variables

The tables include the correlations across the independent variables within models used in section 1 of the analysis.

Full Results, Net Returns as Dependent Variable

Table 12: Full Results, Net Returns as Dependent Variable, Singel Index Model

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.3653	0.4169	0.2909	0.4525	1.0837***	0.2815	0.6887*	1.1044***	0.3551
	(0.4025)	(0.4200)	(0.3836)	(0.4331)	(0.3069)	(0.4563)	(0.2838)	(0.2844)	(0.3566)
Corp	1.3051***	0.7385***	0.8208***	0.8152***	0.7364***	1.3014***	0.7192***	0.7227***	0.7737***
	(0.0337)	(0.0207)	(0.0226)	(0.0216)	(0.0238)	(0.0358)	(0.0235)	(0.0236)	(0.0226)
R^2	.7217	.5935	.5526	.6272	.6244	.7072	.6071	.6075	.6520

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.4997	0.6488	0.7040*	−0.7285	0.1461	0.0596	0.2838	0.5813*	−0.2605
	(0.3518)	(0.3517)	(0.3531)	(0.4731)	(0.2741)	(0.3346)	(0.2802)	(0.2496)	(0.2632)
Corp	0.7738***	0.7741***	0.7774***	1.5136***	0.7961***	1.4336***	0.8299***	0.8147***	0.5274***
	(0.0224)	(0.0224)	(0.0225)	(0.0427)	(0.0218)	(0.0433)	(0.0226)	(0.0226)	(0.0276)
R^2	.6524	.6525	.6527	.7183	.6946	.7736	.6800	.6830	.4172

This table displays the full results from the Single Index Model with net returns as the dependent variable.

Table 13: Full Results, Net Returns as Dependent Variable, Elton et al. (1995) Model

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.5155	0.5021	0.4508	0.5704	1.2039***	0.4898	0.8385*	1.2555**	0.4866
	(0.4296)	(0.4667)	(0.3782)	(0.3695)	(0.2854)	(0.5515)	(0.3965)	(0.3930)	(0.3910)
Stock	−0.0001	0.0011	−0.0013	−0.0019	−0.0019	−0.0021	−0.0017	−0.0017	−0.0016
	(0.0026)	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0028)	(0.0018)	(0.0018)	(0.0015)
Corp	1.2185***	0.8044***	0.9369***	0.8383***	0.7422***	1.2559***	0.7602***	0.7661***	0.8021***
	(0.0558)	(0.0541)	(0.0489)	(0.0416)	(0.0418)	(0.0619)	(0.0429)	(0.0429)	(0.0415)
Term	0.0204	−0.0442*	−0.0805***	−0.0291	−0.0211	−0.0088	−0.0425*	−0.0438*	−0.0336*
	(0.0284)	(0.0219)	(0.0238)	(0.0174)	(0.0197)	(0.0266)	(0.0183)	(0.0183)	(0.0150)
Credit	−0.1436*	−0.1402***	−0.2078***	−0.1171**	−0.1127*	−0.1954**	−0.1635***	−0.1661***	−0.1383***
	(0.0651)	(0.0382)	(0.0571)	(0.0442)	(0.0452)	(0.0632)	(0.0410)	(0.0412)	(0.0362)
R^2	0.7394	0.6007	0.5621	0.6338	0.6342	0.7250	0.6213	0.6218	0.6623

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.6311	0.7807*	0.8365*	−0.2648	0.3577	0.4778	0.4855	0.7374*	−0.0091
	(0.3909)	(0.3908)	(0.3924)	(0.3370)	(0.2905)	(0.2844)	(0.3165)	(0.3479)	(0.2942)
Stock	−0.0016	−0.0016	−0.0016	−0.0054***	−0.0016	−0.0047**	−0.0019	−0.0007	−0.0016
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0014)	(0.0017)	(0.0017)	(0.0017)	(0.0011)
Corp	0.8032***	0.8041***	0.8078***	1.2378***	0.8041***	1.2659***	0.8754***	0.8586***	0.6337***
	(0.0415)	(0.0414)	(0.0415)	(0.0656)	(0.0343)	(0.0552)	(0.0359)	(0.0379)	(0.0503)
Term	−0.0341*	−0.0345*	−0.0347*	0.0654*	−0.0353**	0.0194	−0.0522***	−0.0444**	−0.0891***
	(0.0150)	(0.0150)	(0.0151)	(0.0317)	(0.0110)	(0.0234)	(0.0127)	(0.0147)	(0.0171)
Credit	−0.1389***	−0.1396***	−0.1404***	−0.3627***	−0.2249***	−0.3586***	−0.2226***	−0.1870***	−0.3072***
	(0.0363)	(0.0363)	(0.0365)	(0.0790)	(0.0308)	(0.0600)	(0.0338)	(0.0371)	(0.0445)
R^2	0.6627	0.6628	0.6630	0.8152	0.7332	0.8508	0.7043	0.7001	0.4706

This table displays the full results from the Elton et al. (1995) Model, with net returns as the dependent variable

Table 14: Full Results, Net Returns as Dependent Variable, Bessembinder et al. (2009) Model

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.4810	0.3710	0.2152	0.4127	1.1124***	0.3889	0.7160*	1.1309***	0.3490
	(0.4294)	(0.3955)	(0.3650)	(0.4346)	(0.3207)	(0.4204)	(0.3038)	(0.2983)	(0.3182)
Sov.	0.1496***	0.0525**	0.0787*	0.0629**	0.0686**	0.1487***	0.0781**	0.0786**	0.0670**
	(0.0354)	(0.0201)	(0.0326)	(0.0243)	(0.0222)	(0.0380)	(0.0263)	(0.0272)	(0.0234)
10y+	0.0540*	−0.0002	−0.0201	0.0049	0.0224*	0.0430*	0.0170	0.0171	0.0107
	(0.0221)	(0.0144)	(0.0108)	(0.0123)	(0.0102)	(0.0204)	(0.0102)	(0.0101)	(0.0115)
5-10y	0.1845***	0.1311**	0.1223***	0.1173***	0.1075***	0.1898***	0.1033***	0.1036**	0.1129***
	(0.0513)	(0.0425)	(0.0371)	(0.0349)	(0.0302)	(0.0513)	(0.0307)	(0.0322)	(0.0318)
3-5y	0.3790***	0.2290***	0.2792***	0.2843***	0.2137***	0.4220***	0.2228***	0.2206***	0.2802***
	(0.0660)	(0.0483)	(0.0564)	(0.0476)	(0.0431)	(0.0664)	(0.0410)	(0.0418)	(0.0445)
0-3y	0.3759*	0.3738**	0.5160**	0.3933*	0.2966*	0.2970	0.2650*	0.2751*	0.2714
	(0.1773)	(0.1390)	(0.1778)	(0.1700)	(0.1322)	(0.2034)	(0.1347)	(0.1386)	(0.1389)
R^2	0.7475	0.6098	0.5625	0.6382	0.6332	0.7324	0.6228	0.6231	0.6681

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.4930	0.6418*	0.6971*	−0.2786	0.2086	0.3910	0.2914	0.5738	−0.2440
	(0.3130)	(0.3180)	(0.3194)	(0.3378)	(0.2627)	(0.2768)	(0.2842)	(0.3306)	(0.2610)
Sov.	0.0668**	0.0670**	0.0674**	0.4497***	0.1622***	0.3590***	0.1174***	0.0965***	0.1552***
	(0.0237)	(0.0235)	(0.0236)	(0.0466)	(0.0257)	(0.0410)	(0.0220)	(0.0237)	(0.0323)
10y+	0.0107	0.0107	0.0108	0.0560**	0.0117	0.0453**	0.0063	0.0108	−0.0251*
	(0.0114)	(0.0114)	(0.0115)	(0.0187)	(0.0082)	(0.0160)	(0.0093)	(0.0100)	(0.0106)
5-10y	0.1129***	0.1128***	0.1133***	0.1210***	0.0643*	0.1329**	0.0920**	0.0953**	0.0239
	(0.0318)	(0.0318)	(0.0320)	(0.0353)	(0.0299)	(0.0414)	(0.0325)	(0.0339)	(0.0273)
3-5y	0.2794***	0.2785***	0.2789***	0.4427***	0.2437***	0.4772***	0.3147***	0.2920***	0.2301***
	(0.0446)	(0.0446)	(0.0448)	(0.0841)	(0.0452)	(0.0643)	(0.0461)	(0.0472)	(0.0430)
0-3y	0.2743*	0.2775*	0.2803*	0.0375	0.3626**	0.0577	0.2985*	0.3432*	0.2249
	(0.1398)	(0.1394)	(0.1401)	(0.1345)	(0.1381)	(0.1452)	(0.1482)	(0.1576)	(0.1264)
R^2	0.6685	0.6686	0.6687	0.8168	0.7385	0.8575	0.7159	0.7119	0.4805

This table displays the full results from the Bessembinder et al. (2009) Model with net returns as the dependent variable.

Table 15: Full Results, Net Returns as Dependent Variable, Quadratic programming Bessembinder et al. (2009) model

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
Alpha	0.5455	0.2767	0.2190	0.3509	0.9812	0.4342	0.5745	0.9936	0.2328
$Sov.$	0.1435	0.0609	0.0752	0.0686	0.0809	0.1444	0.0913	0.0915	0.0778
10y+	0.0557	0	0	0.0033	0.0190	0.0442	0.0132	0.0135	0.0076
5-10y	0.1886	0.1219	0.0992	0.1134	0.0992	0.1927	0.0944	0.0950	0.1056
3-5y	0.4197	0.1668	0.2611	0.2453	0.1311	0.4506	0.1336	0.1340	0.2069
0-3y	0.1924	0.6504	0.5645	0.5694	0.6699	0.1681	0.6675	0.6660	0.6020
R^2	0.7463	0.6029	0.5612	0.6357	0.6197	0.7318	0.6068	0.6082	0.6581

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
Alpha	0.5701	0.7201	0.7778	-0.0279	0.3053	0.6593	0.3977	0.6843	-0.3171
Sov.	0.1281	0.1281	0.1285	0.4911	0.2087	0.4103	0.1697	0.1494	0.1901
$Alpha$	0.3777	0.5276	0.5848	-0.1282	0.1386	0.4593	0.2143	0.5007	-0.4085
$Sov.$	0.0776	0.0777	0.0779	0.4372	0.1687	0.3531	0.1246	0.1033	0.1586
10y+	0.0077	0.0077	0.0078	0.0713	0.0099	0.0511	0.0043	0.0089	0
5-10y	0.1056	0.1056	0.1062	0.1343	0.0599	0.1386	0.0872	0.0907	0
3-5y	0.2068	0.2065	0.2081	0.3573	0.1995	0.4572	0.2662	0.2460	0.0764
0-3y	0.6023	0.6025	0.5999	0	0.5620	0	0.5178	0.5512	0.7650
R^2	0.6587	0.6589	0.6594	0.8147	0.7348	0.8570	0.7119	0.7082	0.4435

This table displays the full results from the Quadratic programming on Bessembinder et al. (2009) Model with net returns as the dependent variable.

Appendix 2

Below we present the three steps in estimating the Fama & MacBeth (1973) estimators.

Step one understanding the independent variables and the dependent variable.

In the first step we present the calculated age, expense ratio, log size and log(Size)^2 and the estimated value of Alpha and TR^2. The alpha and TR^2 are estimated using the Bessembinder et al. (2009) model. Table 16 to Table 21 shows the independent variables. The procedure by Amihud & Goyenko (2013) requires lagged independent variables. The dependent variable alpha is shown in Table 22.

Table 16: Step 1: Calculated Age

	HY1	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	13.76	14.25	14.76	15.24	15.75	16.24	16.74	17.23	17.72	18.22	18.71	19.20	19.71	20.20	20.69	21.20	21.70	22.20	22.70	23.19
AB	16.50	16.99	17.50	17.99	18.49	18.98	19.48	19.98	20.46	20.96	21.45	21.94	22.45	22.95	23.44	23.95	24.45	24.94	25.44	25.93
Car	18.52	19.01	19.52	20.00	20.50	21.00	21.50	21.99	22.47	22.98	23.47	23.96	24.47	24.96	25.45	25.96	26.46	26.96	27.46	27.95
Danske	13.33	13.82	14.33	14.81	15.32	15.81	16.31	16.80	17.28	17.79	18.28	18.77	19.28	19.77	20.26	20.77	21.27	21.77	22.27	22.76
DNBK	2.61	3.10	3.61	4.09	4.59	5.09	5.59	6.08	6.56	7.07	7.56	8.05	8.56	9.05	9.54	10.05	10.55	11.05	11.55	12.04
DNBL20	5.19	5.68	6.19	6.67	7.18	7.67	8.17	8.67	9.15	9.65	10.14	10.63	11.14	11.64	12.13	12.63	13.14	13.63	14.13	14.62
DNB	18.34	18.82	19.33	19.82	20.32	20.82	21.32	21.81	22.29	22.79	23.29	23.78	24.28	24.78	25.27	25.78	26.28	26.78	27.28	27.76
DNBIII	9.42	9.90	10.41	10.90	11.40	11.90	12.40	12.89	13.37	13.87	14.37	14.85	15.36	15.86	16.35	16.86	17.36	17.85	18.36	18.84
DNB20I	19.81	20.30	20.81	21.29	21.80	22.29	22.79	23.28	23.77	24.27	24.76	25.25	25.76	26.25	26.75	27.25	27.76	28.25	28.75	29.24
DNB20II	11.28	11.77	12.28	12.77	13.27	13.76	14.27	14.76	15.24	15.74	16.24	16.72	17.23	17.73	18.22	18.73	19.23	19.72	20.22	20.71
DNB20III	5.62	6.11	6.62	7.10	7.61	8.10	8.60	9.09	9.58	10.08	10.57	11.06	11.57	12.06	12.55	13.06	13.56	14.06	14.56	15.05
DNB20IV	2.61	3.10	3.61	4.09	4.59	5.09	5.59	6.08	6.56	7.07	7.56	8.05	8.56	9.05	9.54	10.05	10.55	11.05	11.55	12.04
Handel	5.24	5.73	6.24	6.73	7.23	7.72	8.22	8.72	9.20	9.70	10.19	10.68	11.19	11.69	12.18	12.68	13.19	13.68	14.18	14.67
KLP3	12.78	13.27	13.78	14.26	14.77	15.26	15.76	16.25	16.74	17.24	17.73	18.22	18.73	19.22	19.72	20.22	20.73	21.22	21.72	22.21
KLP5	12.45	12.93	13.44	13.93	14.43	14.93	15.43	15.92	16.40	16.90	17.40	17.88	18.39	18.89	19.38	19.89	20.39	20.88	21.39	21.87
NordII	14.53	15.02	15.53	16.01	16.52	17.01	17.51	18.01	18.49	18.99	19.48	19.97	20.48	20.98	21.47	21.97	22.48	22.97	23.47	23.96
NordIII	1.85	2.34	2.85	3.33	3.84	4.33	4.83	5.33	5.81	6.31	6.80	7.29	7.80	8.30	8.79	9.29	9.80	10.29	10.79	11.28
Par	7.50	7.98	8.49	8.98	9.48	9.98	10.48	10.97	11.45	11.95	12.45	12.93	13.44	13.94	14.43	14.94	15.44	15.93	16.44	16.92

This table shows the age for each fund in every half year (HY) period between October 2006 and September 2016.
The age is computed by deducting inception date from the beginning date of each half year period.

Table 17: Step 1: Calculated Expense Ratio

	HY1	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	0.60	0.60	0.60	0.60	0.61	0.61	0.61	0.61	0.61	0.61	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
AB	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
Car	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Danske	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.42	0.35
DNBK	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
DNBL20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
DNB	0.80	0.80	0.77	0.76	0.67	0.61	0.61	0.61	0.60	0.60	0.61	0.61	0.60	0.60	0.55	0.51	0.50	0.50	0.50	0.50
DNBIII	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
DNB20I	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
DNB20II	0.35	0.35	0.35	0.35	0.35	0.35	0.36	0.36	0.35	0.35	0.35	0.35	0.36	0.36	0.35	0.35	0.35	0.35	0.35	0.36
DNB20III	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
DNB20IV	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.14	0.14	0.14	0.15
Handel	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
KLP3	0.21	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.15	0.10	0.10	0.10
KLP5	0.21	0.22	0.22	0.22	0.21	0.21	0.21	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.15	0.10	0.10	0.10
NordII	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
NordIII	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.18	0.20	0.17	0.15
Par	0.50	0.50	0.50	0.50	0.47	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.46	0.46	0.46	0.46	0.45	0.45	0.46	0.46

This table shows the expense ratio for each fund in every half year (HY) period between October 2006 and September 2016. The expense ratio is calculated as the mean of daily observations in the 125-day rolling window of each half year period.

Table 18: Step 1: Calculated Log(Size)

	HY1	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	18.78	18.61	18.47	18.66	18.86	18.87	18.74	18.82	18.84	18.91	18.82	18.48	18.49	18.72	18.70	18.93	19.50	19.69	18.95	18.93
AB	20.74	20.73	21.42	21.23	20.98	20.31	20.20	20.31	20.29	21.07	21.37	21.42	21.74	21.99	22.16	22.36	22.48	22.60	22.67	22.78
Car	19.58	19.53	19.36	19.21	19.18	19.35	19.42	19.56	19.66	19.62	19.38	19.36	19.18	19.92	19.85	19.83	19.83	19.69	20.04	20.08
Danske	19.31	19.28	19.47	19.54	20.11	20.09	19.95	20.13	20.34	20.41	20.49	20.64	20.76	20.86	20.98	21.09	21.17	21.19	21.25	21.36
DNBK	18.97	19.34	19.48	19.58	19.86	20.47	20.82	21.02	21.22	21.29	21.30	21.40	21.61	21.80	22.02	22.27	22.53	22.57	22.64	22.65
DNBL20	20.64	20.56	20.76	20.59	20.62	20.72	21.09	21.31	21.13	21.15	21.20	21.23	21.23	21.31	21.69	21.68	21.55	21.51	20.52	20.22
DNB	18.93	18.95	18.99	18.56	18.66	18.73	18.89	19.22	19.22	19.40	19.55	19.82	20.73	20.74	20.75	21.29	21.41	21.14	21.08	21.29
DNBIII	20.91	20.99	21.23	21.30	21.52	21.97	22.11	22.24	22.39	22.44	22.55	22.73	22.88	22.88	22.93	23.12	23.25	23.26	23.26	23.33
DNB20I	20.82	20.78	20.66	20.62	20.83	20.76	20.74	20.78	20.78	20.59	20.56	20.61	19.93	19.83	19.77	19.81	19.86	19.77	19.63	19.30
DNB20II	18.96	19.04	19.22	19.17	19.36	19.25	18.98	19.00	18.89	18.71	18.62	18.67	18.69	18.67	18.56	18.58	18.61	18.57	18.69	18.96
DNB20III	20.39	20.36	20.40	20.45	20.52	20.51	20.48	20.52	20.30	20.15	19.88	19.77	19.59	19.46	19.33	19.21	19.20	19.28	19.56	19.77
DNB20IV	22.56	22.51	22.44	22.37	22.59	22.47	22.47	22.54	22.50	22.42	22.35	22.30	22.28	22.42	22.65	22.86	22.81	22.81	22.75	22.80
Handel	18.33	18.30	18.32	18.31	18.42	18.39	18.75	19.00	19.02	19.27	19.64	19.86	19.91	20.08	20.20	20.35	20.90	21.11	21.18	21.20
KLP3	19.03	19.03	19.09	19.11	19.31	19.44	19.49	19.44	19.42	19.48	19.55	19.65	19.68	19.71	19.88	20.49	20.62	20.62	20.66	20.75
KLP5	17.36	17.23	17.28	17.34	18.09	18.41	18.34	18.52	18.71	18.84	19.19	19.53	19.78	19.98	20.00	20.73	20.95	20.98	21.04	21.14
NordII	20.38	20.28	20.44	20.43	20.08	20.56	20.86	21.20	20.94	20.95	21.28	21.47	21.62	21.93	22.00	22.12	21.98	21.99	21.98	21.73
NordIII	19.68	19.94	20.43	20.54	20.43	20.76	20.88	20.83	20.83	21.00	21.15	21.41	21.74	21.81	21.75	21.57	21.80	21.88	22.00	22.00
Par	20.00	19.90	19.97	19.84	20.37	20.28	20.22	19.82	19.73	19.39	19.31	19.32	19.15	18.68	18.51	18.40	18.42	18.64	18.64	18.65

This table shows the age for each fund in every half year (HY) period between October 2006 and September 2016. The age is computed by deducting inception date from the beginning date of each half year period.

Table 19: Step 1: Calculated Log(Size)^2

	HY1	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	352.8	346.4	341.3	348.0	355.6	356.0	351.2	354.1	355.0	357.4	354.4	341.5	341.8	350.4	349.7	358.2	380.3	387.7	359.0	358.2
AB	430.0	429.8	458.8	450.9	440.1	412.5	408.2	412.6	411.6	443.8	456.5	458.7	472.6	483.7	491.0	499.9	505.6	510.7	513.8	519.0
Car	383.4	381.6	374.8	368.9	367.7	374.6	377.1	382.5	386.5	384.9	375.6	374.7	367.9	397.0	394.0	393.2	393.3	387.7	401.8	403.3
Danske	372.7	371.8	378.9	382.0	404.6	403.7	398.0	405.3	413.6	416.7	419.8	426.1	431.1	435.0	440.1	444.7	448.3	449.2	451.5	456.1
DNBK	360.0	374.0	379.4	383.2	394.3	419.0	433.4	441.6	450.2	453.1	453.5	457.8	466.8	475.4	485.1	495.9	507.4	509.5	512.6	513.1
DNBL20	426.2	422.8	430.9	423.9	425.1	429.3	444.6	454.3	446.6	447.3	449.4	450.7	450.8	454.1	470.2	469.9	464.6	462.5	420.9	409.0
DNB	358.3	359.3	360.8	344.4	348.3	351.0	356.9	369.3	369.3	376.3	382.3	392.9	429.7	430.0	430.5	453.2	458.4	447.0	444.2	453.3
DNBIII	437.3	440.8	450.8	453.5	463.0	482.6	488.6	494.5	501.5	503.4	508.4	516.4	523.5	523.4	525.7	534.5	540.4	540.9	541.1	544.5
DNB20I	433.5	432.0	427.0	425.3	433.9	430.8	430.3	431.8	431.6	423.9	422.6	424.6	397.0	393.2	390.7	392.5	394.4	390.8	385.4	372.4
DNB20II	359.6	362.5	369.4	367.4	374.9	370.5	360.4	361.1	356.7	350.1	346.5	348.5	349.2	348.5	344.6	345.2	346.5	345.0	349.3	359.5
DNB20III	415.9	414.4	416.1	418.4	421.3	420.5	419.6	421.2	412.0	406.0	395.1	390.8	383.8	378.7	373.5	369.1	368.8	371.9	382.4	390.8
DNB20IV	508.8	506.7	503.5	500.3	510.4	504.7	504.8	508.2	506.5	502.4	499.4	497.4	496.4	502.5	513.2	522.5	520.5	520.4	517.4	520.0
Handel	336.1	334.8	335.8	335.3	339.3	338.1	351.5	360.8	361.8	371.5	385.7	394.2	396.4	403.0	408.0	414.0	437.0	445.5	448.6	449.5
KLP3	362.1	362.2	364.4	365.2	373.0	377.7	379.8	377.9	377.2	379.6	382.1	386.0	387.2	388.6	395.1	420.0	425.3	425.2	426.9	430.6
KLP5	301.3	296.9	298.7	300.6	327.1	338.8	336.3	343.2	349.9	355.0	368.3	381.6	391.4	399.1	399.9	429.6	439.1	440.2	442.8	446.7
NordII	415.4	411.2	417.8	417.4	403.0	422.8	434.9	449.3	438.4	439.0	452.6	461.1	467.6	481.0	484.0	489.5	483.2	483.4	483.3	472.3
NordIII	387.3	397.5	417.6	421.8	417.3	430.9	436.1	434.0	433.8	440.9	447.1	458.3	472.7	475.7	473.0	465.5	475.1	478.8	484.0	484.0
Par	399.9	396.0	399.0	393.7	415.0	411.2	408.8	393.0	389.1	376.1	373.0	373.2	366.7	349.0	342.8	338.6	339.3	347.4	347.6	348.0

This table shows computed Log (Size)^2 for each fund in every half year (HY) period between October 2006 and September 2016.

Table 20: Step 1: Estimated $Alpha$

	HY1	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	-0.07	-2.39	-2.09	-5.60	2.32	5.34	0.31	-0.22	-0.20	-1.37	1.28	3.27	3.32	1.91	2.25	1.26	-1.95	-3.80	-0.65	1.53
AB	-0.37	-1.68	-1.73	-7.61	-1.14	8.48	2.28	0.57	0.69	-3.25	1.08	3.30	3.04	2.06	2.18	1.51	-1.39	-2.58	-0.86	2.17
Car	-0.43	-1.54	-2.04	-3.94	3.12	2.46	0.01	-0.54	0.73	-0.13	2.14	4.44	2.73	0.30	0.57	1.29	-1.30	-2.99	1.28	0.65
Danske	-0.18	-1.41	-2.21	-2.89	3.34	4.43	-1.13	-1.11	1.38	-1.72	1.43	2.79	2.68	0.84	1.51	0.32	-1.17	-3.58	1.75	1.51
DNBK	-0.09	-1.31	-1.29	-2.27	-0.12	9.85	0.71	1.74	1.90	0.28	2.45	2.29	3.03	2.05	2.31	1.29	-0.99	-2.97	0.82	3.15
DNBL20	-0.05	-1.43	-1.89	-6.14	4.46	5.96	-1.24	0.42	0.70	-0.91	2.10	2.21	2.06	0.90	0.88	0.01	-1.73	-3.46	1.20	2.26
DNB	-0.49	-1.66	-2.55	-5.50	-0.32	9.22	1.04	0.94	1.50	-0.35	2.10	2.22	3.01	2.03	1.86	1.06	-1.36	-2.82	-0.11	3.58
DNBIII	0.11	-1.07	-1.93	-4.97	0.09	9.64	1.42	1.35	1.90	0.05	2.50	2.62	3.43	2.44	2.24	1.37	-1.06	-2.55	0.19	3.89
DNB20I	-0.46	-1.54	-1.62	-3.66	3.79	3.85	-0.68	0.22	-0.46	0.29	1.84	1.93	2.21	0.83	1.36	0.27	-1.41	-3.29	1.30	1.65
DNB20II	-0.32	-1.41	-1.45	-3.51	3.95	3.98	-0.54	0.33	-0.31	0.43	1.98	2.07	2.35	0.98	1.50	0.42	-1.26	-3.14	1.43	1.82
DNB20III	-0.16	-1.26	-1.30	-3.36	4.10	4.12	-0.41	0.49	-0.15	0.58	2.13	2.22	2.50	1.13	1.63	0.58	-1.11	-3.00	1.58	1.93
DNB20IV	-0.11	-1.21	-1.25	-3.33	4.16	4.19	-0.36	0.54	-0.11	0.63	2.18	2.28	2.56	1.18	1.70	0.63	-1.06	-2.96	1.64	2.00
Handel	-1.24	-0.89	-0.75	-4.06	0.94	0.95	-1.65	-0.62	-0.63	-1.39	0.22	2.29	-0.17	0.76	0.12	2.48	-1.93	-3.90	-0.29	1.35
KLP3	0.02	-1.02	-1.08	-3.36	3.33	1.97	-0.30	0.37	0.34	0.45	0.89	0.98	0.50	0.21	0.28	0.04	-1.16	-1.86	1.05	0.85
KLP5	0.04	-0.54	0.25	-2.10	-0.03	1.25	-0.75	0.47	-0.00	-0.03	1.56	1.68	0.97	0.79	0.81	0.32	-1.69	-2.83	1.04	1.40
NordII	-0.36	-0.96	-1.15	-3.33	2.95	4.14	-0.98	0.08	0.64	-0.59	1.05	1.67	0.74	0.49	0.84	0.09	-1.24	-2.96	0.78	0.98
NordIII	-0.33	-0.92	-1.20	-3.28	2.95	4.64	-0.43	0.53	1.09	-0.49	1.42	2.10	1.55	1.22	1.50	0.54	-0.96	-3.59	0.73	1.73
Par	-0.42	-0.77	-1.34	-2.63	1.33	2.40	2.00	1.52	-0.32	0.38	0.10	0.72	0.26	0.07	0.27	-0.21	-0.81	-1.41	0.44	-0.23

This table shows the estimated alpha for each fund in every half year (HY) using the Bessembinder et al. (2009) model. The time period for the estimation is between October 2006 to September 2016. The estimates are based on net of returns. The table is a result of 20*18 regressions. The alpha will be used as an independent variable reflecting persistence ($Alpha$) as shown in equation 13.

Table 21: Step 1: Estimated TR^2

	HY1	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	2.51	2.47	2.09	1.55	1.97	1.60	1.68	2.33	2.17	2.45	2.39	2.38	1.65	2.05	1.67	2.22	2.95	2.42	2.05	1.73
AB	2.14	2.15	2.07	1.05	1.27	1.30	1.29	2.16	2.03	1.81	1.96	1.73	1.37	1.94	1.28	1.71	2.79	1.98	1.34	0.61
Car	1.92	1.57	0.93	0.99	2.06	1.55	0.72	1.12	1.29	2.30	0.46	-0.37	0.50	1.20	1.25	0.16	3.28	1.92	1.83	1.75
Danske	2.37	1.84	1.31	1.43	2.08	0.87	0.58	1.27	1.35	2.15	1.59	1.12	0.80	1.99	1.67	2.32	2.74	0.91	1.53	1.27
DNBK	2.21	2.09	1.59	1.77	1.54	0.53	1.15	1.39	1.52	2.55	1.89	1.77	1.38	1.99	1.76	2.11	3.25	1.81	1.88	1.34
DNBL20	2.54	2.58	1.74	1.41	2.20	1.25	1.15	1.74	1.90	2.68	2.09	2.28	1.77	2.70	2.78	2.58	3.69	2.61	2.47	2.28
DNB	2.66	2.42	1.53	1.23	1.53	0.62	1.17	1.37	1.66	2.57	1.99	1.67	1.05	2.01	1.86	2.14	3.04	1.85	1.60	1.24
DNBIII	2.64	2.41	1.53	1.23	1.53	0.62	1.17	1.37	1.66	2.57	2.00	1.68	1.06	2.00	1.87	2.14	3.04	1.85	1.61	1.24
DNB20I	2.87	2.29	1.64	1.67	2.23	1.22	1.08	1.51	0.48	2.00	1.64	1.54	1.09	2.04	1.81	2.12	3.27	1.75	1.57	1.36
DNB20II	2.86	2.29	1.63	1.67	2.23	1.22	1.08	1.52	0.48	2.00	1.64	1.55	1.09	2.04	1.82	2.13	3.27	1.75	1.57	1.36
DNB20III	2.86	2.29	1.63	1.67	2.23	1.22	1.08	1.51	0.49	2.00	1.64	1.55	1.09	2.04	1.82	2.13	3.28	1.76	1.57	1.36
DNB20IV	2.86	2.29	1.63	1.67	2.23	1.22	1.08	1.51	0.49	2.00	1.64	1.55	1.09	2.04	1.82	2.13	3.28	1.75	1.57	1.36
Handel	1.48	2.65	2.33	2.63	2.33	1.77	1.75	3.01	2.42	2.54	2.87	2.56	2.33	2.54	2.33	1.24	3.50	2.72	2.29	2.90
KLP3	2.76	2.27	2.02	1.66	2.48	1.71	1.71	2.55	2.37	2.53	2.02	2.14	2.19	2.22	0.16	2.66	3.39	2.62	2.08	2.13
KLP5	3.82	4.13	2.83	3.33	2.47	2.25	1.81	2.63	2.36	2.89	2.60	2.63	2.54	2.85	2.34	3.03	3.93	3.14	2.36	2.50
NordII	2.15	2.27	2.15	2.18	1.37	1.21	1.37	1.99	1.85	2.26	2.06	2.06	2.24	1.95	2.19	2.15	2.96	1.81	2.09	2.13
NordIII	1.81	1.95	1.85	1.88	1.90	1.26	1.35	1.85	1.75	2.22	2.08	1.93	2.00	1.88	2.03	2.13	2.89	1.27	1.65	1.94
Par	2.29	2.57	1.70	1.32	2.04	0.13	-0.16	0.41	1.58	1.74	0.64	-0.34	-0.51	0.24	0.98	1.38	2.10	1.39	0.77	1.47

This table shows the estimated TR^2. By using the Bessembinder et al. (2009) model, we first estimate the R^2 and then the variable is transformed according to equation (13). As per Amihud and Goyenko (2013) the TR^2 estimations reflect selectivity in funds. The table is a result of 20*18 regressions. This is because we have 20 half year periods and 18 funds.

Table 22: Step 1: **Understanding the Dependent variable α**

	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
ABL	-2.39	-2.09	-5.60	2.32	5.34	0.31	-0.22	-0.20	-1.37	1.28	3.27	3.32	1.91	2.25	1.26	-1.95	-3.80	-0.65	1.53
AB	-1.68	-1.73	-7.61	-1.14	8.48	2.28	0.57	0.69	-3.25	1.08	3.30	3.04	2.06	2.18	1.51	-1.39	-2.58	-0.86	2.17
Car	-1.54	-2.04	-3.94	3.12	2.46	0.01	-0.54	0.73	-0.13	2.14	4.44	2.73	0.30	0.57	1.29	-1.30	-2.99	1.28	0.65
Danske	-1.41	-2.21	-2.89	3.34	4.43	-1.13	-1.11	1.38	-1.72	1.43	2.79	2.68	0.84	1.51	0.32	-1.17	-3.58	1.75	1.51
DNBK	-1.31	-1.29	-2.27	-0.12	9.85	0.71	1.74	1.90	0.28	2.45	2.29	3.03	2.05	2.31	1.29	-0.99	-2.97	0.82	3.15
DNBL20	-1.43	-1.89	-6.14	4.46	5.96	-1.24	0.42	0.70	-0.91	2.10	2.21	2.06	0.90	0.88	0.01	-1.73	-3.46	1.20	2.26
DNB	-1.66	-2.55	-5.50	-0.32	9.22	1.04	0.94	1.50	-0.35	2.10	2.22	3.01	2.03	1.86	1.06	-1.36	-2.82	-0.11	3.58
DNBIII	-1.07	-1.93	-4.97	0.09	9.64	1.42	1.35	1.90	0.05	2.50	2.62	3.43	2.44	2.24	1.37	-1.06	-2.55	0.19	3.89
DNB20I	-1.54	-1.62	-3.66	3.79	3.85	-0.68	0.22	-0.46	0.29	1.84	1.93	2.21	0.83	1.36	0.27	-1.41	-3.29	1.30	1.65
DNB20II	-1.41	-1.45	-3.51	3.95	3.98	-0.54	0.33	-0.31	0.43	1.98	2.07	2.35	0.98	1.50	0.42	-1.26	-3.14	1.43	1.82
DNB20III	-1.26	-1.30	-3.36	4.10	4.12	-0.41	0.49	-0.15	0.58	2.13	2.22	2.50	1.13	1.63	0.58	-1.11	-3.00	1.58	1.93
DNB20IV	-1.21	-1.25	-3.33	4.16	4.19	-0.36	0.54	-0.11	0.63	2.18	2.28	2.56	1.18	1.70	0.63	-1.06	-2.96	1.64	2.00
Handel	-0.89	-0.75	-4.06	0.94	0.95	-1.65	-0.62	-0.63	-1.39	0.22	2.29	-0.17	0.76	0.12	2.48	-1.93	-3.90	-0.29	1.35
KLP3	-1.02	-1.08	-3.36	3.33	1.97	-0.30	0.37	0.34	0.45	0.89	0.98	0.50	0.21	0.28	0.04	-1.16	-1.86	1.05	0.85
KLP5	-0.54	0.25	-2.10	-0.03	1.25	-0.75	0.47	-0.00	-0.03	1.56	1.68	0.97	0.79	0.81	0.32	-1.69	-2.83	1.04	1.40
NordII	-0.96	-1.15	-3.33	2.95	4.14	-0.98	0.08	0.64	-0.59	1.05	1.67	0.74	0.49	0.84	0.09	-1.24	-2.96	0.78	0.98
NordIII	-0.92	-1.20	-3.28	2.95	4.64	-0.43	0.53	1.09	-0.49	1.42	2.10	1.55	1.22	1.50	0.54	-0.96	-3.59	0.73	1.73
Par	-0.77	-1.34	-2.63	1.33	2.40	2.00	1.52	-0.32	0.38	0.10	0.72	0.26	0.07	0.27	-0.21	-0.81	-1.41	0.44	-0.23

This table shows the alpha for each fund from half year 2. (HY2). The estimates for every half year period shown in this table are annualized. As the procedure by Amihud and Goyenko (2013) requires lagged independent variables, the HY1 variables in tables 19 to 24 will be the first lagged variables. Therefore, the alpha can only be the dependent variable from HY2 onwards.

Step two for estimating the coefficients.

The dependent variable α for all funds will now be regressed on the lagged independent variables for all funds. This is shown in equation below.

$$\alpha_{\mathtt{t}} = \gamma + \gamma \mathtt{TR}_{t-1}^{2} + \gamma \mathtt{Alpha}_{t-1} + \gamma \mathtt{log(Size)}_{t-1} + \gamma \mathtt{log(Size)}^{2}{}_{t-1} + \gamma \mathtt{Age}_{t-1} + \gamma \mathtt{Exp}_{t-1} + \epsilon_t \tag{17}$$

For instance, α_{HY2} is regressed on the $\text{TR}^2{}_{HY1}$, Alpha_{HY1}, log(Size)_{HY1}, $\text{log(Size)}^2{}_{HY1}$, Age_{HY1}, and Expense Ratio_{HY1}. As we have 19 half year periods this means that the procedure is repeated 19 times (HY2 to HY20). Table 23 shows the results from this step.

Table 23: Step 2: Cross Sectional Regressions Coefficient Results

	HY2	HY3	HY4	HY5	HY6	HY7	HY8	HY9	HY10	HY11	HY12	HY13	HY14	HY15	HY16	HY17	HY18	HY19	HY20
Constant	-2.34	28.89	-15.79	-93.78	-11.16	22.15	0.01	-46.29	71.27	6.79	9.28	87.78	35.88	6.31	-23.16	19.45	41.41	-7.03	64.70
TR^2_{t-1}	0.30	0.25	-3.08	-0.19	-4.84	-0.85	0.07	-0.05	-0.86	0.67	-0.10	-0.01	0.36	-0.16	0.06	-0.25	-0.50	-0.78	0.71
$Alpha_{t-1}$	-0.82	0.59	2.64	0.27	-0.22	0.13	0.55	0.25	0.05	0.31	0.58	0.70	0.41	1.02	0.10	-0.30	0.36	-0.35	0.17
$\log(Size)_{t-1}$	0.13	-2.88	2.50	9.57	2.13	-2.24	0.14	4.35	-6.45	-1.08	-0.92	-8.86	-3.72	-0.53	2.15	-2.00	-4.06	1.13	-6.69
$\log(Size)^2_{t-1}$	-0.00	0.07	-0.07	-0.23	-0.04	0.06	-0.00	-0.10	0.15	0.04	0.02	0.22	0.09	0.01	-0.05	0.05	0.10	-0.03	0.17
Age_{t-1}	-0.01	-0.00	-0.02	0.05	-0.06	0.03	-0.03	0.03	0.02	0.03	0.00	0.01	-0.04	0.01	-0.04	-0.01	0.05	0.03	0.00
Expense $Ratio_{t-1}$	-1.63	-0.99	0.16	-3.51	1.48	1.10	-1.83	-0.44	-4.22	0.50	2.43	1.05	2.12	-0.66	2.50	-0.21	-2.02	-4.53	1.68
R^2	0.536	0.801	0.712	0.283	0.656	0.468	0.710	0.236	0.638	0.449	0.370	0.570	0.852	0.828	0.285	0.527	0.511	0.725	0.375

This model includes the regression results of the cross-sectional analysis, as presented in equation 17. The table represents the result of step 2 of the procedure. The model is dependent on the data set estimated in step 1 of the procedure. The underlying pricing model scheme used to measure the data set of variables in step one is the Bessembinder et al. (2009) model. Furthermore, the step one procedure use net returns. The exact model specifications can be viewed in equation (8). The table is a result of 20 cross-sectional regressions, based on 20 half year periods t.

Step three mean of the second step regressions.

Table 24: Step 3 Average of the coefficients from cross sectional regression

	Bessembinder et al. (2009) model
Constant	10.22
TR^2	-0.49
Alpha	0.34
log(Size)	-0.91
$\log(\text{Size})^2$	0.02
Age	0.00
Expense Ratio	0.36
R^2	0.55

This table represents step three of the procedure to calculate the Fama & MacBeth (1973) estimators. The result in this table is equal to the presentation of Bessembinder et al. (2009) model for net returns in Table 9. This is one example of the procedure done for each model specification on net and gross returns as shown in table 10.

Appendix 3

Credit Rating Based Model

Table 25: Credit Rating Model

Panel A, Gross return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
$Alpha$	1.1556*	1.3705***	1.3020***	1.3059**	1.6139***	0.5593	1.8817***	1.7165***	1.1222***
	(0.5719)	(0.3919)	(0.3447)	(0.4292)	(0.3119)	(0.5447)	(0.3300)	(0.3310)	(0.3212)
AAA	0.5046***	0.2872***	0.3333***	0.3440***	0.2816***	0.4710***	0.2888***	0.2884***	0.3248***
	(0.0849)	(0.0549)	(0.0610)	(0.0663)	(0.0487)	(0.0794)	(0.0485)	(0.0487)	(0.0500)
AA	0.2390	0.2323*	0.2560*	0.1783	0.1599	0.2874	0.1610	0.1619	0.1906
	(0.1274)	(0.1035)	(0.1048)	(0.0972)	(0.0828)	(0.1504)	(0.0862)	(0.0862)	(0.1002)
A	0.2241***	0.1382***	0.1386***	0.1244***	0.1119***	0.1657***	0.1034***	0.1046***	0.0814***
	(0.0656)	(0.0333)	(0.0305)	(0.0324)	(0.0279)	(0.0450)	(0.0261)	(0.0262)	(0.0228)
BBB	0.1448*	0.0414	0.0442	0.0939*	0.0882*	0.1647*	0.0672	0.0677	0.0887*
	(0.0602)	(0.0354)	(0.0409)	(0.0410)	(0.0358)	(0.0649)	(0.0356)	(0.0357)	(0.0383)
$ST1X$	−0.1395	0.3591	0.9280**	0.3585	0.3293	−0.0635	0.4228	0.4639*	0.1057
	(0.4444)	(0.2803)	(0.3183)	(0.2585)	(0.2021)	(0.4393)	(0.2299)	(0.2319)	(0.2593)
$S1-5$	−0.0246	0.0306	0.0642	0.0441	0.0556*	0.0552	0.0572*	0.0574*	0.0789**
	(0.0307)	(0.0301)	(0.0375)	(0.0240)	(0.0234)	(0.0428)	(0.0278)	(0.0279)	(0.0305)
$S5-10$	0.1272***	0.0257	0.0130	0.0290*	0.0307*	0.1009***	0.0348**	0.0347**	0.0259
	(0.0209)	(0.0152)	(0.0160)	(0.0139)	(0.0124)	(0.0235)	(0.0132)	(0.0133)	(0.0135)
R^2	0.7368	0.5963	0.5661	0.6329	0.6320	0.7202	0.6189	0.6196	0.6642

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
$Alpha$	1.1230***	1.1275***	1.1353***	0.4427	0.7411*	0.8265*	0.9943***	1.1788***	0.7112*
	(0.3188)	(0.3185)	(0.3198)	(0.3172)	(0.3263)	(0.3214)	(0.2642)	(0.3090)	(0.3022)
AAA	0.3244***	0.3247***	0.3253***	0.3562***	0.2590***	0.3750***	0.3051***	0.3187***	0.2258***
	(0.0501)	(0.0502)	(0.0503)	(0.0683)	(0.0479)	(0.0662)	(0.0507)	(0.0532)	(0.0484)
AA	0.1908*	0.1906*	0.1913*	0.4054**	0.2133*	0.4076**	0.2615*	0.2223*	0.1773*
	(0.0971)	(0.0970)	(0.0973)	(0.1276)	(0.0828)	(0.1508)	(0.1053)	(0.0965)	(0.0841)
A	0.0816***	0.0817***	0.0826***	0.1326*	0.0718*	0.1030*	0.0470*	0.0639*	−0.0471
	(0.0229)	(0.0229)	(0.0230)	(0.0538)	(0.0292)	(0.0448)	(0.0230)	(0.0262)	(0.0255)
BBB	0.0887*	0.0888*	0.0892*	0.0601	0.0620	0.0938	0.0716	0.0857*	0.0066
	(0.0377)	(0.0377)	(0.0378)	(0.0479)	(0.0330)	(0.0557)	(0.0373)	(0.0378)	(0.0256)
$ST1X$	0.1198	0.1312	0.1355	0.3931	0.2403	0.1499	0.4956*	0.4263	0.2757
	(0.2574)	(0.2575)	(0.2585)	(0.3327)	(0.3022)	(0.2744)	(0.2279)	(0.2327)	(0.2087)
$S1-5$	0.0787**	0.0786**	0.0789**	0.0538	0.1120***	0.0892	0.0863**	0.0800**	0.2080***
	(0.0299)	(0.0299)	(0.0300)	(0.0543)	(0.0306)	(0.0503)	(0.0318)	(0.0277)	(0.0491)
$S5-10$	0.0258	0.0257	0.0258	0.2877***	0.0635***	0.2198***	0.0524***	0.0411**	0.0163
	(0.0135)	(0.0135)	(0.0135)	(0.0202)	(0.0137)	(0.0220)	(0.0142)	(0.0132)	(0.0143)
R^2	0.6646	0.6647	0.6648	0.8104	0.7346	0.8450	0.7066	0.7012	0.5010

Panel B, Net return analysis

	ABL	AB	Car	Danske	DNBK	DNBL20	DNB	DNBIII	DNB20I
α	0.5556	0.7705*	0.9520**	0.8059	1.4139***	0.5593	1.0817**	1.5165***	0.6222

	DNB20II	DNB20III	DNB20IV	Handel	KLP3	KLP5	NordII	NordIII	Par
α	0.7730*	0.9275**	0.9853**	−0.0073	0.5411	0.6265	0.7943**	1.0285***	0.2115

This table displays the full results for gross returns and only the alpha for net returns for the Credit Rating Model. Similar to the Bessembinder et al. (2009) model, this model divides the credit premium in letter based corporate indices and term premium in maturity based government indices.