Lappeenranta-Lahti University of Technology LUT

School of Business and Management

Strategic Finance and Business Analytics

Factor investing in the Nordic corporate bond markets

Master's thesis

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ABSTRACT

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This thesis studies factor investing in Nordic corporate bond markets. The countries selected into the scope are Sweden, Norway, Finland and Denmark with the time period of 2010 – 2020. The examined factors include momentum, value, carry and low-risk, which is measured with two proxies. Also, multifactor portfolios consisting of several different single factor portfolios are constructed and compared. The long-only factor portfolios are compared in terms of excess returns, Sharpe ratio, skewness- and kurtosis- adjusted Sharpe ratio (SKASR), tracking error and information ratio. After this, the portfolio excess returns are regressed against the benchmark index to derive the CAPM alpha for the portfolio. Finally, the multifactor alphas controlling for several explanatory factors are calculated.

The results show that the carry factor generates the best performance among all portfolios during the sample period. Portfolios consisting of bonds with high maturity and momentum have also good performance and produce significant alphas. The alphas for carry and momentum factors uphold also when controlled with several different risk premiums. In addition to the single factor portfolios, multifactor portfolios also performed well, generating relatively high excess returns, high Sharpe ratios as well as significant CAPM alphas. Two of the multifactor portfolios also generated significant multifactor alphas.

TIIVISTELMÄ

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Hakusanat: faktori-sijoittaminen, yrityslainamarkkinat, momentum, riski, carry, arvo

Tämän tutkimuksen tarkoitus on tutkia faktori-sijoittamista pohjoismaalaisilla yrityslainamarkkinoilla. Tutkimukseen valitut maat ovat Ruotsi, Norja, Suomi sekä Tanska ja tutkimuksen aikaväli on 2010 - 2020. Tutkitut faktorit ovat momentum, arvo, carry sekä riski, jota mitataan kahdella eri mittarilla. Yksittäisistä faktori-portfolioista kasataan myös monia faktoreita sisältäviä yhdistelmä-portfolioita joiden suoriutumista arvioidaan. Faktori-portfolioita vertaillaan riskittömän koron ylittävän tuoton, Sharpe luvun, SKASR:n, ja muiden indikaattorien avulla. Portfolioiden tuottoja analysoidaan myös regressioanalyysin avulla yhden ja usean selittävän muuttujan avulla.

Tutkimuksen tulosten perusteella carry-faktori suoriutuu parhaiten tutkitulla ajanjaksolla. Pitkän juoksuajan ja vahvan momentumin yrityslainainoja sisältävät portfoliot suoriutuivat myös hyvin, ja tuottivat tilastollisesti merkitsevää ylituottoa. Ylituotto carry- ja momentum-faktoreille säilyi myös, kun sitä kontrolloitiin usealla selittävällä muuttujalla. Yksittäisistä faktoreista koostuneiden portfolioiden lisäksi myös useamman faktorin portfoliot suoriutuivat hyvin. Niillä oli verrattain korkea riskittömän koron ylittävä tuotto, hyvät Sharpe luvut sekä tilastollisesti merkittävä ylituotto yhden selittävän muuttujan regressioissa. Kaksi portfoliota säilytti ylituottonsa myös, kun sitä kontrolloitiin usealla selittävällä muuttujalla.

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1. Introduction

Factor investing is a strategy in which the investor chooses instruments on the basis of their characteristics. It is based on the idea that an assets' returns can be attributed to underlying explicit factors, such as firm attributes, macroeconomic factors or style factors and on the realization that the assets are bundles of these factors. Furthermore, the returns of the assets are driven by these underlying attributes that also reflect different risks and rewards. As with any investing strategy, the goal is to produce excess returns compared to the market. In factor investing this is commonly done by forming portfolios consisting of different securities on the basis of what factors are seen to produce the best returns. (Koedijk, Slage & Stork, 2016)

In the past, empirical research on factors has primarily been focused to equity markets, starting from the studies published by Fama and French (1992; 1993) in the early 1990s. In fact, Harvey, Liu and Zhu (2016) recognized over 300 papers that focus on cross-section returns in the equities. It is safe to say that factor investing in equity markets has been fairly thoroughly studied when compared to the corporate bond markets. As Bektic, Wenzler, Schiereck & Spielmann (2016) state, there is not that much documented evidence on factors in the corporate bond markets as on the stock markets. However, some studies have shown that similar type of factors that produce excess returns in the equity markets can also produce excess returns in the bond markets. [For example, Jostova et al. (2013), Houweling & Van Zundert (2017) and Israel et al. (2018)] As the research on corporate bond markets is not that comprehensive, the aim of this thesis is to extend the research and present more evidence on the subject.

The thesis is organized as follows. The first section consists of the introduction, background, research questions and the limitations set to this thesis. The key terms and other general theoretical background will also be presented. Next, in the second section the literature review will present the previous studies and their results. The third section goes through the factors that are studied in this thesis more specifically and discusses how the factors are measured and possible alternative metrics. The fourth section describes the data used in the study and discusses the methodology. The

empirical results are described in the fifth section, and finally the sixth section concludes the thesis.

1.1 Background

The most basic concept to look into in regards to this thesis is corporate bonds itself: what they are, why they are issued and what kind of markets they are traded in. The most simple description of corporate bonds is that they are tradeable debt instruments that are issued by non-government borrowers. The issuers use the debt capital markets to raise capital for short and/or long-term projects and requirements. The bonds that are issued are then traded in the primary and secondary markets. Most of the issued corporate bonds are vanilla instruments that pay a fixed coupon and have a fixed maturity date. The bond's yield is set by the markets (for example in the book building process) and reflects the credit quality of the issuer as well as other qualities of the bond such as supply and demand, general market conditions and level of liquidity. (Choudhry, 2001, 320-321)

The risks that corporate bonds are exposed to are credit risk, interest rate risk, liquidity risk and prepayment (or early redemption) risk. The first means the risk that the company that has issued the bond cannot fulfill its obligations and cannot pay the interest or the nominal value to the holder of the bond. The second one means the risk that interest rate changes pose to the value of the bond. When interest rates increase in the market, in theory the value of the bond should decrease. The third risk is related to the risk that the holder of the bond cannot sell it because there are no buyers in the market. Lastly, the prepayment risk means the chance that the issuer redeems the bond early, before its initially set maturity date before the interest rates fall. (Bertocchi, Consigli, D'Ecclesia, Giacometti, Moriggia & Ortobelli, 2014, 21)

The size of the corporate bond market is significant: as Bai, Bali and Wen (2019) point out, the size of the corporate bond market in the US is 12 trillion USD when measured considering outstanding bonds whereas the size of the equity market is 19 trillion USD.

What should be considered however, is that corporate bond issuances exceed equity issuances by a significant multiple (1,3 trillion USD versus 265 billion USD) in the time period of 2010 – 2019. Also, when looking with a wider scope, the size of the whole bond market including government bonds and bonds issued by other market participants such as sovereigns, supranationals and agencies is 48 trillion USD as of 2020 (Federal reserve, 2021).

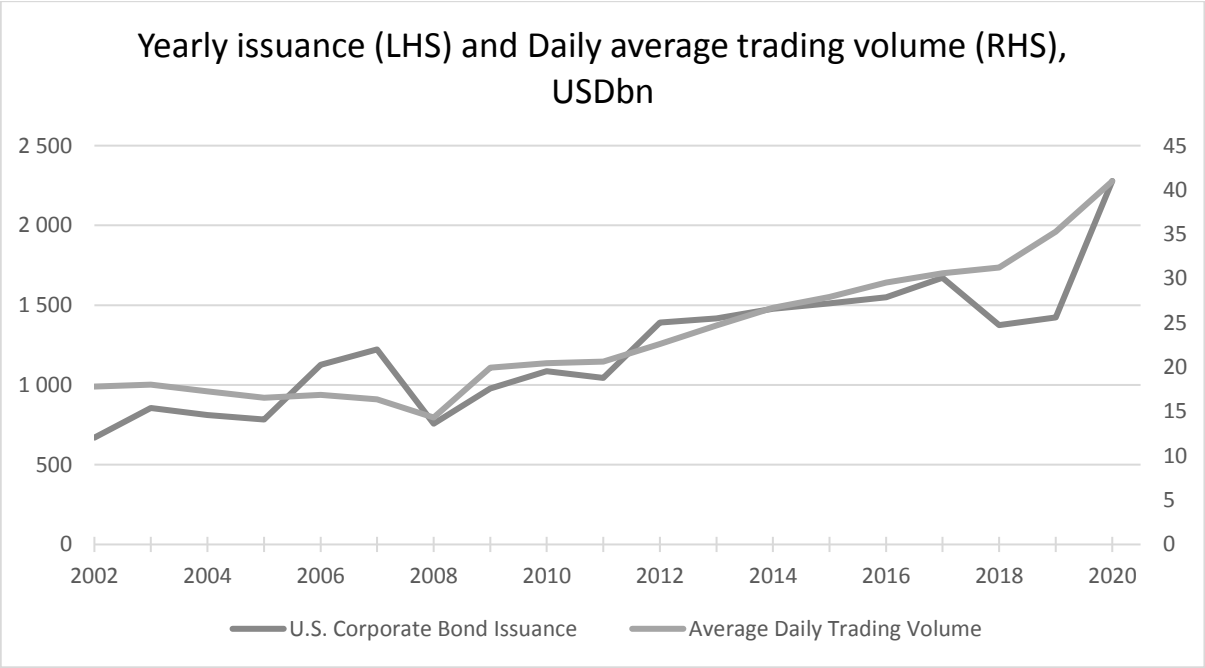

Figure 1. Yearly issuance and Daily average trading volume of corporate bonds in the US in period 2002 - 2020, USDbn. (SIFMA, 2021a & 2021b)

SIFMA's (Securities Industry and Financial Markets Association) (2021a) statistics show that the growth of corporate bond issuance has been rapid in the last 10 years, as the amount has more than doubled in the period of 2010 – 2020 from 1085 billion USD to 2280 billion USD. The growth of the market is also reflected in the trading volume as the SIFMA's statistics (2021b) also show that the average daily trading volume has doubled in the same time period with the volume increasing from 20,5 billion USD to 41 billion USD.

1.2 Overview of Nordic bond markets

The Nordic corporate bond market can be described as growing, stable and transparent market with strong and predictable political institutions and companies. It is characteristic for the market that most issuances have a maximum maturity of 5 years, and only a few as long as 7 – 10 years. It is common for the bonds to not have a rating as 54% of issuers are unrated. However, one reason for this is that there are plenty of external opinions available for credit quality of the companies and an official rating would not add considerable benefit. (Evli, 2019) In Credit Suisse's year 2017 yearbook, Swedish, Danish, Norwegian and Finnish bonds' real returns over the period of 2000 – 2016 were reported, being 5,7%, 6,0%, 4,3% and 6,5% p.a., respectively. The corresponding figure for United States was 5,1% and 4,8% for world. (Credit Suisse, 2017) The figures show that Nordic bonds have mostly yielded better returns when comparing to the rest of the world, and even to the US.

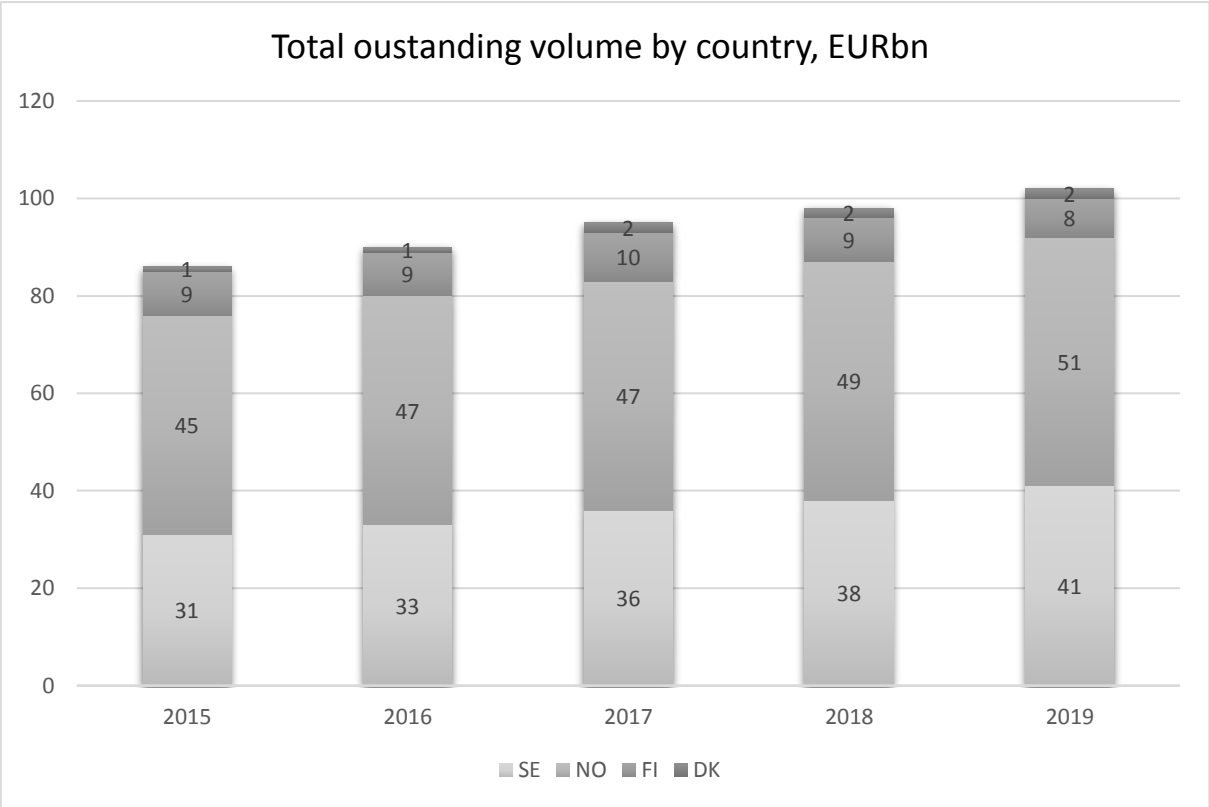

Figure 2. Total outstanding volume by country, EURbn (Nordic trustee, 2020)

Nordic trustee (2020) has estimated the whole Nordic bond market to be 1122 billion EUR when measured with the total outstanding amount at the year end of 2019. The size of the corporate bond market was 102 billion EUR (9% of the whole market) of which 51 billion Eur (50%) was issued by Norwegian companies, 41 billion EUR (40%) by Swedish, 8 billion EUR (8%) by Finnish and finally 2 billion EUR (2%) by Danish corporates. The growth rate of the market has been 4% annually since 2015 with Sweden being the key driver in the change.

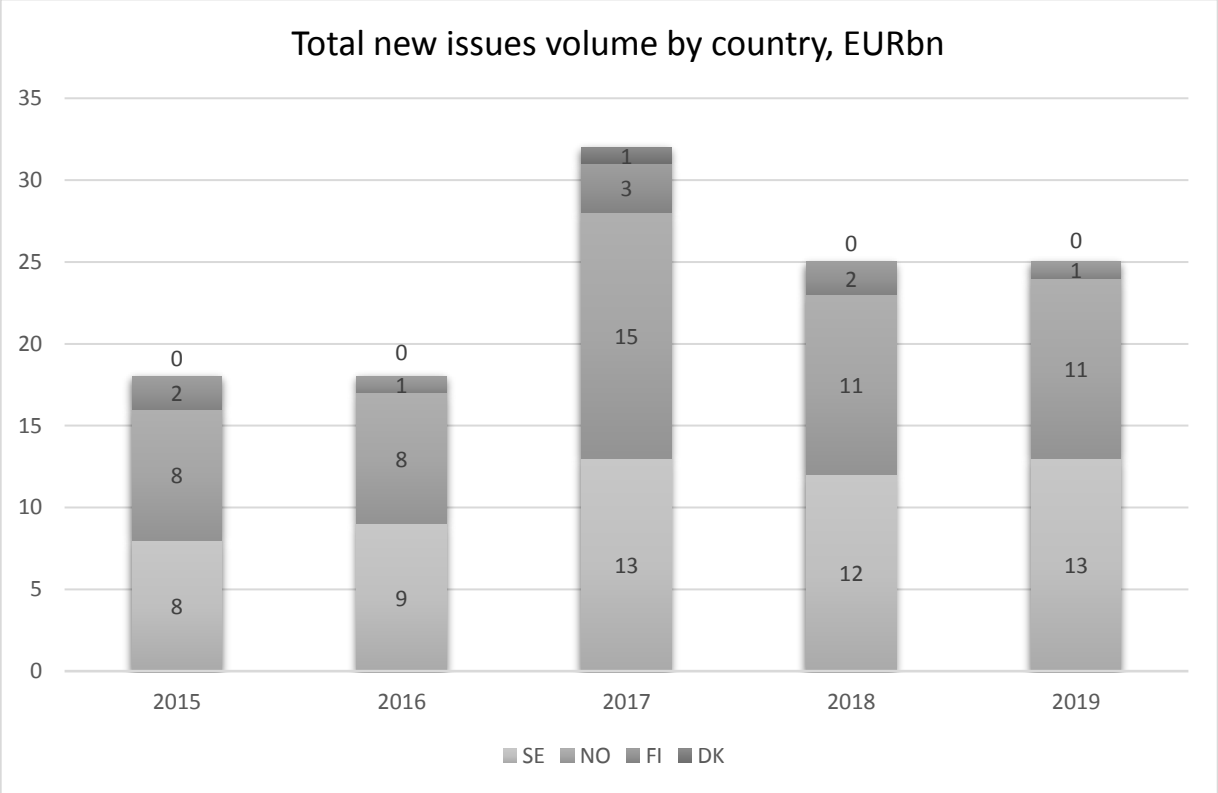

Figure 3. Total new issues volume by country, EURbn (Nordic Trustee, 2020)

When looking at the volume of new issuances, the average growth in period of 2015-2019 has been a bit over 13% annually, while the volume has been approximately 24 billion EUR. As shown in Figure 3, the volume of issuance has varied significantly between the years. For example, in 2017, over 70% more bonds were issued than in

2016. When comparing to the United States' figures showed earlier, Nordic countries share the same trend of growth in issued bonds.

1.3 Research objectives, questions, and hypothesis

The literature review of this thesis shows evidence that it is possible to earn abnormal returns on corporate bond markets with factor investing. This thesis aims to fill the gap in the research by studying specifically publicly traded bonds of Nordic companies, which have not been studied before, to the best of my knowledge. The main research question is:

- Is it possible to achieve abnormal returns in Nordic corporate bond markets with the use of different factors?

After the answer to the main question has been found, the thesis will focus on the sub-questions which are:

- Which factors perform the best or worst?
- How do multifactor portfolios perform?
- Which multifactor portfolio combination produces the best results?

The specific factors that will be studied empirically are momentum, low-risk, value and carry. These will be discussed more specifically in the literature review. The thesis also aims to produce new information on how to measure the mentioned factors and whether the measures are viable in practice. The hypothesis of the research is that there are bond-related factors enabling excess returns. The thesis will also study whether the possible abnormal returns, or alpha, will diminish when controlled for several different risk premia.

1.3.1 Limitations

The limitations that are set for this study mostly stem from the real world constraints. The aim is to derive results that are applicable not only theoretically but also practically. Because in practice the shorting of corporate bonds is difficult and costly, please see for example Houweling and Van Zundert (2017) and Bektic et al. (2016), long-only portfolios are analyzed in this thesis. The inclusion of mixed portfolios could inflate the theoretically achievable benefits more than what would be realistic in real world situations. The difficulties in shorting corporate bonds stems from the fact that the bonds that are desired to be shorted are often illiquid and low-rated which causes operational difficulties and high transaction costs. The challenges of shorting corporate bonds were also discussed by Asquith, Au, Covert and Pathak (2013).

Issuing company specific factors such as company leverage, profitability or equity volatility are excluded from the study as this allows the use of bonds issued by non-listed companies. It is likely though, that including the aforementioned variables could improve the results of this study as they would provide more information on the quality of the issuer companies and relative value of the bonds.

Some limitations stem from the availability of data. For example, because only a minority of the bonds in the collected dataset have a rating given by a credit rating agency, it is not possible to use it in constructing the factors and another variable is needed to be used as a proxy. As mentioned earlier, Evli's (2019) report on the Nordic corporate bond market discloses that only a minority of the issued bonds in the market have a rating so the dataset mirrors the real life situation.

Transaction costs that occur when the bonds are traded of course affect the real-life returns of portfolios. Harris (2015) has estimated these costs to be 85 basis points for retail-sized trades and 52 basis points for larger trades on average. The data he used was from the corporate bond markets in the United States. It appears that there has not been a similar study done on the transaction costs on the Nordic markets, but it would be reasonable to assume that the costs are not lower as the Nordic market is not

as liquid and there is less competition in terms of brokers. The transaction costs are out of scope in this thesis as estimating them would be considerably laborious and such data is not available.

A perfect dataset would also have a more even number of bonds outstanding across the full sample period, which is unfortunately not the case with the dataset of this thesis as more bonds are outstanding in the end of the period than in the beginning of the period. Of course, a longer time period of the study would be beneficial but is also not possible to do because of the lack of data. Furthermore, in the literature, investment grade and high-yield bonds are usually separately analyzed as their risk profiles and clientele differ from each other. Once again, the separation could improve the results of the thesis but cannot be done viably as the bonds are not categorized.

1.4 Theoretical framework, key terms and concepts

This section goes through the key terms, concepts and the theoretical background that is needed to fully understand the remainder of this thesis. The framework this thesis is as displayed in Figure 4. The thesis draws elements from fixed income investing, factor investing and the Nordic corporate bond markets, to produce new evidence on the existence of factors in the market.

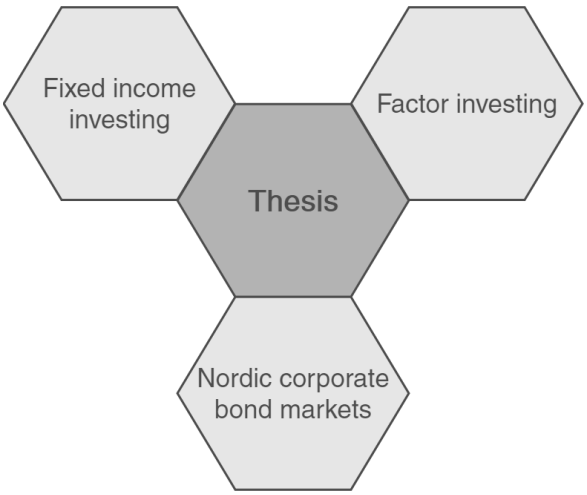

Figure 4. The framework of disciplines covering this thesis

As mentioned in the introduction, the theoretical background on factor investing is majorly influenced by the original research of Fama and French (1992; 1993). The literature has of course vastly expanded since and research considering factors in corporate bonds has emerged too. This research background is reviewed in the literature review, whereas the Nordic corporate bond markets were discussed and described in the earlier chapter. Fixed income investing can basically be characterized as the practice of investing in instruments that yield an interest to its holder. There is a broad range of participants that make up the fixed income markets that can largely be divided into borrowers and lenders. These participants include different financial institutions, retail investors, governments, municipalities and other organizations. (Choudry, 2001, 3-5)

1.4.1 Yield curve

When yields of bonds having an equal credit rating are plotted against maturity dates, we can derive a line that is called the yield curve. When the curve has an upward slope, it is considered to be normal and when it is sloping downward it is considered inverted. Understanding the yield curve is important because when calculating the individual carries of the bonds we make an assumption that the curve is flat. The method might not be the most optimal, but it is the best of the available solutions.

There are plenty of ways to utilize the yield curve. It acts as an indicator for future yield levels and gives out implications of the market's view on the direction of future interest rates or inflation levels. The curve is used also in measuring and comparing the returns of different maturities and to analyze the relative value between bonds of same maturity. Lastly, the yield curve is used to price interest rate derivatives, such as FRAs (future rate agreements).

Sometimes the term term structure of interest rates is also used when referencing to yield curve. Strictly speaking this is not correct as the term structure should be reserved for the zero-coupon yield curve. (Choudry, 2001, 102-103)

1.4.2 Sharpe ratio and Skewness and Kurtosis Adjusted Sharpe Ratio (SKASR)

Sharpe ratio, called then as the reward/variability ratio, was originally innovated by William Sharpe (1966) in his paper Mutual fund performance. The ratio is a method to measure the performance of for example a fund or portfolio of investments and as the name suggests is calculated by dividing the return of the portfolio (reward) with the standard deviation of the portfolio (variability). The form is displayed below:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

Where R_p = return of portfolio

R_f = risk-free rate

σ_p = standard deviation of the portfolio

Sharpe ratio is used as the performance measure and as a tool to compare the portfolios with in this thesis as it is the go-to option in the literature and industry and, as said, is extremely widely used. Even though the Sharpe ratio is a commonplace measure of performance it has some flaws: for example, it does not take properly into account that the returns in many cases are not normally distributed. This underlying mechanic causes that for example right-skewed return distributions are penalized which can cause biases in the results. In this thesis, skewness and kurtosis-adjusted Sharpe ratio (SKASR), introduced by Pätäri (2011) is used alongside the Sharpe ratio. As the name suggests SKASR takes into account the third (skewness) and fourth (kurtosis) moments of return distributions and consequently gives out better and more reliably comparable results. To calculate SKASR, adjusted Z-value by Cornish and Fisher (1937) is obtained:

$$Z_{cf} = Z_c + \frac{1}{6}(Z_C^2 - 1)S + \frac{1}{24}(Z_C^3 - 3Z_C)K - \frac{1}{36}(2Z_C^3 - 5Z_C)S^2$$

Where Z_c = Critical value for the probability based on standard normal distribution

S = Skewness of the distribution

K = Kurtosis of the distribution

The formulas for skewness and kurtosis are the following:

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{r_{it} - \bar{r}_i}{\sigma}\right)^3$$

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{r_{it} - \bar{r}_i}{\sigma}\right)^4 - 3$$

Where N = number of outcomes

$\bar{r}_i$ = average return

After these have been calculated, skewness and kurtosis adjusted deviation (SKAD) is derived with formula:

$$SKAD = \sigma * \frac{Z_{CF}}{Z_c}$$

Finally, we can calculate SKASR with formula:

$$SKASR = \frac{r_p - r_f}{SKAD_p^{(\frac{ER}{|ER|})}}$$

Where $SKAD_p$ = Skewness and kurtosis-adjusted deviation of the monthly excess of portfolio p

ER = Average excess returns of portfolio p

The formula is adjusted to take account the possibility of validity problem caused by negative excess returns with the modification of Israelsen (2005).

1.4.3 Tracking error

Tracking error is a measure of how much a portfolio or fund deviates from a specified benchmark, for example an index. It can be used to evaluate the performance of a fund

manager or a portfolio. Tracking error can also be called active risk. The lower the tracking error is, the more accurately it follows the movements of the benchmark. Respectively, if the tracking error is large it signals that the portfolio's returns have fluctuated strongly in regard to the benchmark. (Rompotis 2011)

$$Tracking\ error\ (TE) = \sqrt{\frac{\sum_{i=1}^{n}\left(R_p - R_B\right)^2}{n-1}}$$

Where R_p= return of portfolio

R_B = return of benchmark index

n = number of periods

Usually the tracking error is reported at annual level. If one wishes to transform for example monthly tracking error into yearly, she should do it by multiplying the monthly tracking error with a square root of 12.

The interpretation or tracking error is not completely straightforward. Research has shown that funds that have a high tracking error also produce higher alpha than funds with lower tracking error. When using tracking error, one should also focus on what kind of investing strategy is evaluated. For example, some funds (eg. index-funds) focus on minimizing the tracking error. (Israelsen & Cogswell 2007)

1.4.4 Information ratio

Information ratio is another metric to evaluate the performance of a fund or portfolio. It is the average excess return per one unit of volatility in excess return, or in other words it depicts the excess returns that are produced by the portfolio by carrying more risk than the benchmark. (Goodwin 1998) The ratio can be calculated with the help of tracking error with the following formula:

$$Information\ ratio\ (IR) = \frac{R_p - R_B}{TE}$$

Where R_p = return of portfolio

R_B = return of benchmark index

Israelsen and Cogswell (2006) state that the higher the information ratio is, the better is the performance of the portfolio. They also claim that when information ratio is used in conjunction with tracking error one can evaluate portfolios or funds more sensibly. In another paper Israelsen (2005) discusses that the information ratio is best used when comparing the same style or asset class portfolios. He also adds that as it is possible that the excess returns are negative, the formula should be modified to take that into account.

$$Modified\ information\ ratio = \frac{ER}{SD^{\left(\frac{ER}{abs(ER)}\right)}}$$

Where ER = excess returns

SD = standard deviation of the excess returns

Bossert, Füss, Rindler and Schneider (2010) state that information ratio has its limitations but is a useful and reliable measure of performance. They also provided a framework for performance evaluation, where for example British corporate bonds were seen to have below average or poor performance with information ratio of below 0 and good or very good with a ratio of above 1,2. They also agree with Israelsen and Cogswell (2006) that the evaluator should always keep the context in mind when assessing the portfolio or fund.

2. Literature review

The literature on factor investing in corporate bonds is relatively limited, at least when compared to the attention that factor investing in equities has received. This being the case, the former mentioned research also exists and has gained more attention as of late. The following literature review attempts to summarize the most relevant studies on the subject. The review further assists on validating that the research questions and hypothesis of the thesis are constructed correctly and are in congruent with the latest academic research.

As mentioned before, perhaps the most well-known research on factors was authored by Fama and French in years 1992 and 1993. Their studies demonstrated that value, beta and size factors can explain up to 95% of variability in U.S equity market returns. The articles paved the way for numerous other researches on the subject in the following years. In 2015 Fama and French (2015) complemented their original model with two new variables, investment and profitability and showed that the new model performed better than the older one. As this thesis is focused and corporate bond markets, we are primarily interested in the factors that are relevant to bonds. The literature on these factors is in general more recent than the one on equities. Some studies focus more on bond market specific factors such as bond ratings etc. and on the other hand some focus more on the original Fama-French factors and factors that are derived from the equity markets or the issuing companies themselves.

2.1. Research on factors in bond markets

Bektic, Wenzler, Wegener, Schiereck and Spielmann (2016) applied the Fama-French factors to corporate bond market in the U.S. and European credit space. The article focuses on the well documented equity factors and to the link between equities and corporate bonds. The study found that all of the equity factors do not directly have a significant explanatory power on corporate bond markets. The strongest returns were

achieved with profitability and investment factors in the high-yield bonds. L'Hoir and Boulhabel (2010) analyzed momentum, profitability and valuation indicators in the U.K. and euro zone bond markets over the years 2000 - 2008. Valuation was measured by bond spread that was estimated to be either higher or lower than the exposure to common factors should warrant. Momentum was measured by the market consensus opinion revisions of a company's expected cash flows for the current year and net income divided by total assets was used as the measure of profitability. The results indicated that by combining the mentioned factors one can obtain superior performance in the corporate bond market. The evidence was broadened by Chordia, Goyal, Nozawa, Subrahmanyam & Tong (2017) who showed that company level characteristics asset growth, profitability and equity earnings predict bond returns. The factors they studied were size (logarithm of the company's market value), value (book value to market value of equity), momentum (cumulative last 5-month returns), past month's equity return, company accruals and other firm level metrics. The effect of the factors is dampened though once controlled for the Fama-French (2015) factor model.

Houweling and Van Zundert (2017) provided evidence that low-risk, value, size and momentum factor portfolios produce meaningful and statistically significant excess returns. The study was conducted by sorting corporate bonds by the size of the issuing company, the credit rating of the bond, credit spread of the bond, and on the basis of the past returns of the bond. Also, multifactor portfolios were analyzed. Their dataset was rather large (monthly average n = 4993) and consisted of investment grade and high yield corporate bonds that were part of corresponding Barclay's indices over the years 1994 – 2015. The results also showed that breakeven transaction costs are above the actual transactions costs of corporate bonds and that investors already using the factor investing principles in equity investing can increase their alpha by applying the same principles in corporate bond markets.

Israel et al. (2018) also did a comprehensive analysis on common factors in corporate bond returns. The factors studied were quality, carry, value and momentum. The bonds analyzed were the constituents of the Bank of America's investment grade and high-yield corporate bond indices. The results showed that value, carry, defensive and

momentum factors produce positive risk-adjusted returns. The results are consistent with both, long-and-short academic portfolios as well as with more realistic long-only portfolios where the transaction costs are taken into account. Brooks, Palhares and Richardson (2018) further examined the benefits of diversifying of style-based fixed income portfolios. They studied value (option adjusted spread against distance to default and regression model of duration, rating and return volatility spreads), momentum (past six and twelve month returns), carry (option adjusted spread versus treasuries) and defensive/quality (low duration, profitability and leverage) factors. They found that value, momentum and defensive factors produced statistically significant alpha in the corporate bond markets. Furthermore, the combo portfolio which consisted of a collection of the earlier mentioned factors could also produce significant alpha.

Henke, Kaufmann, Messow and Fang-Klinger (2020) did their own extensive study on five different style factors: value, equity momentum, carry, quality and size. They also used the multifactor approach. In the paper they found that the utilization of these style factors could have yielded abnormal returns in the last 20 years when used correctly. The portfolios in the study were long only. Henke et al. used the difference between the option adjusted spread and the estimated fair spread as the signal for corporate bond's value. The fair value was calculated by using different parameters of the issuer company and the bond such as debt to enterprise value ratio, market cap, rating score and modified duration. For momentum factor they used the equity's 3-month momentum to forecast the bonds' returns. For carry they used option adjusted spread and for size the total sum of the market value of bonds outstanding for the issuer company. As the measurement for quality they used 14 different variables from the company's balance sheets. The results showed that multifactor approach would be beneficial for investors as it offers an attractive risk versus return profile. They also found that all of the studied factors had evidence in some subset of the bonds with some factors yielding alphas as high as over 7 percent annually. Asness, Ilmanen, Israel and Moskowitz (2015) claim that among others, momentum, carry, defensive and value are style factors that work "everywhere" on average, across asset classes and markets although in their paper they focused on government, not corporate bonds.

The evidence of carry as a viable factor is shown by Koijen, Moskowitz, Pedersen and Vrugt (2013) who found that it predicts both cross-section and time series returns in bonds. Martens, Beekhuizen, Duyvesteyn and Zomerdijk's (2019) results are also in line with the earlier mentioned ones as they also observed that a strategy that selects bonds based on carry produces significant alpha. They also found that low volatility factor, or betting against beta is not a strong factor. Conversely, Frazzini and Pedersen (2014) showed that betting against beta is a viable strategy in many different asset classes, including corporate bonds. The article proved that assets that have a high beta produce lower alpha compared to assets with lower beta. The difference in results most likely stems from different data used in the analysis. The low risk strategy or the so called betting against beta strategy was also found viable by Ilmanen, Byrne, Gunasekera and Minikin (2004).

Corporate bond characteristics downside risk, liquidity risk and credit risk were proved to have economically and statistically significant returns, by Bai et al. (2019). They argued that as more commonly used factors such as size or default spread are constructed from macroeconomic variables or stock-level data, their predictive power is limited for bond-level returns and one should use prominent features of corporate bonds instead. The factors analyzed in the article positively predicted cross-sectional returns of bonds and portfolios constructed using these factors generated returns greater than other models in the literature. Hammami and Bahri (2016) produced evidence that bond ratings are the most important driver of corporate bond returns in the Tunisian markets. They divided the bonds into portfolios on the basis of their rating and found that also the maturity of the bond is an important variable as short term bonds yielded better returns than long-term bonds on average whereas liquidity had no effect on the returns in their study. A conclusion from the paper could be that as high rating and short maturity signal lower risk, the risk factor does exist on the market in the period that was examined.

2.2 Momentum and trend in corporate bond markets

One of the first comprehensive studies studying purely momentum in corporate bonds was done by Gebhardt, Hvidkjaer and Swaminathan (2005). The key results were that there was no significant evidence of excess momentum returns in investment grade bonds. However, the results indicated that there is evidence of significant reversals. Moreover, there was evidence for a significant momentum spillover from past equity returns to future bond returns. Momentum in corporate bonds was also studied extensively by Jostova et al. (2013) who provided strong evidence that past half-year winners outperform the losers. The profits were achieved in non-investment grade bonds but are non-existent in investment grade bonds.

Lin, Wu and Zhou (2017) commented the results by stating that as high-yield bonds only account for approximately 8% of the bond market the anomaly is not that significant. Their article analyzed momentum in corporate bonds of different ratings to see if the momentum anomaly is present on the whole market and not just in a smaller segment of it. The results indicated that there is evidence of strong momentum in corporate bonds across all ratings, which covers both investment grade and speculative grade bonds and withstands the consideration of transaction costs. In a subsequent study, Lin, Tao, Wang and Wu (2020) again found evidence of momentum in a wide range of corporate bonds by using large dataset derived from five different data vendors. The portfolios were formed on the basis of the bonds' past six-month returns and the results withstood when controlled with risk factors including the Fama-French factors and also the liquidity risk.

Pospisil and Zhang (2010) found evidence that buying corporate bonds with high momentum produces better returns than low momentum ones and that this effect is closely related with credit cycles (contractions and expansions in access to credit). The study was conducted with a wide range of different portfolio formation and holding periods. Ho and Wang (2018) showcased a more complex strategy based on the premise of momentum in their paper in the Journal of Financial Markets. Their approach was to construct a quantile risk (QR) index in order to recognize the turning points for

corporate bonds in the late stages of momentum cycle. In the turning points, the bond prices should be too extreme to justify their fundamental values and by utilizing the index one could be able to buy the winner bonds with low QR and sell the loser bonds with high QR. Their results showed that the approach yielded significant abnormal returns.

Technical analysis methods have also been studied for corporate bonds. For example, Bektic and Regele (2017) showed that trend following strategy incorporated with simple moving average timing execution gave strong and robust excess returns for corporate bonds. The result is consistent with other studies of momentum. Lin, Wu and Zhou (2019) used the moving averages of corporate bond yields with multiple different lag values to obtain trend signals over a time horizon and to construct portfolios on this basis. The results were that there is a significant trend premium, which is stronger among bonds with higher coupon rates and yields, newer issuance and smaller issuance size.

Technical trend-following rules were studied by Montgomery, Raja and Ülkü (2019) with lackluster results as the trend following strategy and the 52-week strategy were both unprofitable. The rules they tested included moving average with several different lag values and MACD. Lastly, Derwall et al. (2009) show that the common risk factors do not predict the returns of short-term maturity bond correctly as they underestimate them. The anomaly sustains even when considering pricing errors, illiquidity and other restrictions.

2.3 Summary of the literature review and conclusions

To summarize the review, when looking purely at the evidence of factors in the corporate bond markets, low risk and momentum have the most credibility. It has been shown that firm level factors also have effect on the returns of the bonds that they have issued. In addition, the carry and value factors have been proved to produce excess returns. In this thesis, the momentum, low risk, carry and value factors will be studied

empirically. The proxies for the mentioned factors varied widely, the ones that are used in this thesis are discussed in the next chapter.

Like mentioned, firm level factors like debt level ratios, cash flow ratios and similar do produce good results on the ground of literature review. The problem with these variables is that the data can be hard to come by and would in practice mean the exclusion of some, if not all un-listed companies from the study. Most of the studies have focused in the so called bond level indicators which is the case in this thesis too. The data for these indicators is much more widely available which means that the results can also be utilized in real life much more plausibly. The former literature has mostly been on American corporate bonds with fewer studies on European data.

3. Factors

Like mentioned earlier in the thesis, a factor can be almost any characteristic that explains a security's return and/or risk component. However, there are some requirements according to scholars that the factor should fulfill to be considered relevant. The factor should exhibit significant explanatory power and be supported by economic rationale. It should also have significant premia that can be expected to continue in the future and that is supported by an economic or behavioral explanation. The factor should exist in different markets and it needs to be implementable in liquid instruments. (Bektic et al. (2016); Ang, Goetzmann & Schaefer 2009; Amenc, Goltz, Lodh & Martellini 2012)

Factors can also be understood as macroeconomic variables that explain and affect the returns of broad range across assets. These should not to be mixed with so called style factors that capture the risks and explain returns within an asset class. These style factors are the ones that this thesis discusses and studies. They can also be called investment factors, dynamic factors, smart beta or alternative beta factors. (Ang 2014, 226) Bender, Briand, Nielsen and Stefek (2010) recognize three groups among factors: asset class, style and strategy. An asset class risk premium is the compensation for

carrying the risk of a broad asset class. An example would be the U.S. equity risk premium or real estate risk. Style factor is defined by them to be the expected return in assets with similar technical or fundamental characteristics, which follows the definition given earlier. Lastly, the returns on strategy factor are generated by following a certain strategy. An example of this could be to carry out an arbitrage in a company merger situation. In general, style factors are usually best utilized in long-short factor portfolios that can harvest the pure factor premiums and avoid most if not all of the asset class risk premiums. However, it is common that factors are used in long-only portfolios. (Blitz 2016)

This section describes the factors studied in this thesis more specifically and discusses how the factors are measured, their calculation formulas and the possible alternative options that could or have been implemented in the research.

3.1 Low risk

Low risk, or defensive factor, is the tendency of assets that have a lower risk to deliver higher returns when compared to the higher risk assets. Asset's risk can be measured with numerous different metrics. Brooks, Palhares and Richardson (2018) measure the riskiness with duration, with low duration bond being the lower risky ones. Israel et al. (2018) built a measure of risk from company variables leverage, profitability and low duration. Houweling and Van Zundert (2017) used low maturity and the bond's rating as the measurement. The short maturity effect has also been documented by Ilmanen et al. (2004) who showed that short-dated corporate bonds produced the highest Sharpe ratios in their study. Also, Derwall (2009) provided evidence that common risk factors underestimate returns of low maturity bonds and that maturity is a good measure for risk. Considering this, in this thesis the bonds' time to maturity will act as one of the measures of the bonds' risk.

The other measure that will be used is the volatility of the bonds' returns. As volatility's effect on the returns of corporate bonds has not been widely documented this study

aims to fill this gap in the research in that regard. The volatility will be calculated from the past 6-month total returns for each bond and the portfolios are sorted to high and low volatility ones.

3.2 Value

The hypothesis with value factor is, that securities that appear to be cheap, on average, outperform securities that appear to be expensive. The premium for the factor is therefore achieved with going long on the cheap assets and shorting the expensive ones. (Asness, Frazzini, Israel, Moskowitz 2015). Vanguard's research report written by Pappas and Dickson (2015) suggests that a rational explanation for the value premium could be that investors see a cyclical risk that security's returns have a positive correlation between economic activity. On the other hand, behavioral explanation, that rises from suboptimal investor behavior is that recency bias causes investors to avoid firms in distress and focus on firms with recent growth instead.

Many different metrics have been used to represent value when investigating different factors in the markets. While the same style of variables have been used in the bond markets and equity markets, this thesis focuses on the factors that can be derived directly from the bonds itself. Therefore, factors such as book value to equity or earnings per share to equity are not applicable.

Out of all the factors mentioned in the literature for corporate bonds, value has probably the most different ways to measure it. The usage of credit spreads (the difference of corporate bonds yield to maturity compared to a government issued bond) has been proved to be valuable, as decreasing spreads have been documented to forecast an upgrade in the bond's rating (Norden & Weber 2004). One prevalent way to construct the factor is to combine various variables, like Israel et al. (2018) did by using credit spread of the bond, its default risk, duration and the volatility of the last 12 month excess returns. Houweling and Van Zundert (2017) compiled their value factor consisting of credit spread changes, life to maturity and the rating of the bond. L'Hoir and Boulhabel

(2010) used bond's spread, credit class and company specific indicators return on equity and volatility of equity.

In this thesis the value will be measured with the three-month change in the bond's credit spread.

$$Value = \frac{Sp_t - Sp_{t-3}}{Sp_{t-3}}$$

Where Sp = credit spread of the bond

The strategy with this factor is that one should invest in the bonds with a decreasing credit spread which is thought to signal a forthcoming rating upgrade, which in turn would make the bond more appealing. This way it would be possible to recognize bonds that are cheap relative to others. While the most ideal factor would probably be a combination of for example the rating of the bond and its spread, it is unfortunately not possible implement with the dataset of this thesis as only a minority of the bonds have been given a rating by a credit rating agency.

3.3 Momentum

In addition to value, momentum is one the most well documented factors in both equity and debt markets. It is the relation between the asset's expected returns and its recent relative performance history (Asness, Moskowitz & Pedersen 2013). According to Asness, Frazzini, Israel and Moskowitz (2014), the momentum premium has evidently been present for over 212 years, from 1801 to 2012 when looking at the U.S. and U.K. equity data. As the literature review shows, momentum phenomenon is present also in the bond markets. In the empirical study we have to make the choice of how the momentum measured. Jostova et al. (2013) and Gebhardt et al. (2005) sorted the bonds according to their past 6-month returns. Asness et al. (2013) used the same method but with 12-month cumulative returns. Pospisil and Zhang (2010) applied a wider range of formation and holding periods (1 - 24 months) in their measure of momentum.

On the other hand, Lin et al. (2017) measured the momentum with several lags of moving averages of the yields and then compiled them into one indicator of the expected returns with linear regressions. This method, contrary to the former, allows the use of multiple trend signals and is not tied to a fixed time period. However, it is more arduous to use and might not be as transparent and intuitive.

When considering the prior research, the conclusion is to use a more simple measure of momentum in the empirical study. The formula for it can be seen below:

$$Momentum = \frac{r_t - r_{t-6}}{r_{t-6}}$$

Where r = total return of the bond

$t - 6$ = time point 6 months ago

While the method is more rigid in the way that it is bound to a fixed period, it has other advantages as it is more applicable and easier to implement. Also, the fact that majority of the past literature has used this method advocates for the use of it also, as the results are more comparable to each other.

3.4 Carry

The fourth single factor to be studied is called carry. Universally carry can be defined as the return from holding a financial instrument. As a factor carry has been used in many asset classes, including for example currency and commodity trading. In the context of bonds, Koijen et al. (2015) define the bond carry as the return of the bond when the yield curve does not change within the holding period. Therefore, the carry can be calculated as the yield spread of the bond and a risk-free instrument and the “roll down”, which is the price increase of the bond as it rolls down the yield curve. In the thesis we follow the example of Koijen et al. (2015) and Martens et al. (2019) in calculating the carry for each bond:

$$C_t = \frac{P_{t+1}^{T-1}(y_t^{T-1}) + D * 1_{(t+1 \in coupon\ dates)} - P_t^T}{P_t^T} - r_t^f$$

$$= y_t^T - r_t^f + \frac{P_{t+1}^{T-1}(y_t^{T-1}) - P_{t+1}^{T-1}(y_t^T)}{P_t^T}$$

$$\cong y_t^T - r_t^f - D^{mod}(y_t^{T-1} - y_t^T)$$

Where C = carry

P = price

y = yield to maturity

D = coupon payment

r^f = risk-free rate

D^{mod} = modified duration

T = time to maturity

The yield spread component is called the slope of the term structure and the roll down is the yield to maturity change between the maturities multiplied by the modified duration. This method assumes that the term structure of interest rates stays constant for all maturities. The bond carry can also be estimated by calculating synthetic futures for the bonds but still, the method makes the same assumption regarding the term structure as the formula above. Carry can be also measured with option-adjusted spread (OAS) like Israel et al. (2018) did in their study. However, the option adjusted spreads are laborious to calculate if they are not available directly from a database and have their own issues as well. For example, OAS is also a precise measure of carry only if the credit curve is flat, as if it has a negative or positive slope, the carry is either under- or overestimated. Considering this, the first mentioned method should give a reasonable measure of carry for this study.

The hypothesis regarding carry as a vehicle to produce excess returns, is that higher carry bonds produce higher returns in the future compared to the bonds with a lower carry. Therefore, in the empirical study the bonds are sorted by their carries in the beginning of the periods and the portfolios are formed on that basis.

3.5 Multifactor portfolio

Lastly, the multifactor portfolio is assembled from the single factor portfolios following the example of Houweling and Van Zundert (2017). The formula for the portfolio returns is simple:

$$Multifactor = 0{,}25r_t^{Factor\ 1} + 0{,}25r_t^{Factor\ 2} + 0{,}25r_t^{Factor\ 3} + 0{,}25r_t^{Factor\ 4}$$

Where r_t = return of portfolio at time t

The factors chosen to the examined multifactor portfolios are determined by the results from the single factor analyses. The goal is of course to find a collection of factors that yield the highest returns, but as multifactor portfolios are also utilized to lower the risk of the investments, the riskiness of the portfolios is also closely analyzed. The hypothesis is that a multifactor portfolio can produce higher risk adjusted returns than a single factor portfolio. The included factors could also be invested in unevenly so that the weights would be for example 40%/40%/10%/10%. The number of factors could also be modified so that the multifactor portfolio would for example include two of five single factors.

4. Data

The dataset for the thesis is downloaded from the Refinitiv Datastream database. The bonds that are included are ones that are issued in the Nordic (Finnish, Swedish, Norwegian and Danish) markets and for which the issuer is a corporate entity. As some Nordic corporate bonds are not listed in the respective countries' markets, but in the international markets instead, the data for these securities was obtained by searching for bonds in the international market with a Nordic issuer. These bonds are a small part of the data. Also, international bonds with the issuing currency of Swedish, Danish or Norwegian krone were searched to make sure the data set was as comprehensive as

possible, and all securities were included. Only fixed or floating rate bonds were selected, and the only instrument type accepted was bond, meaning that convertible or callable etc. instruments were excluded from the dataset.

Altogether, the dataset consists of approximately 900 corporate bonds issued by Nordic companies, ranging from being issued in the 1990s at the earliest to as recent as 2020. Most of the bonds (around 80%) are issued in the 2010s which enables the use of a ten-year long sample period in the study. The maturities (time between the issuance and the redemption of the bond) varies from just a year to 30 years. Approximately half of the bonds have a maturity of 2 – 5 years with over 300 bonds having a maturity of 5 years. Graph displaying the distribution of the maturities can be found in the appendices.

When taking a look at how the bonds are distributed by the issuers' country of domicile, we see that the distribution is very much aligned with how was shown in subsection 1.2. In terms of the number of bond issuances, Swedish and Norwegian bonds make up about 90% of the dataset with Finland having a share of 8%, while the rest being Danish. The figures do not change much when measured by the outstanding amount. The largest change is that Sweden's share is larger, and Finland's and Norway's shares are a bit smaller. The graphs displaying both of the distributions are also shown in the appendices.

The variables in the dataset for each bond are total return index, credit spread, yield to maturity, modified duration and time to maturity. As bonds' returns include the interest yield in addition to the price change of the bond, total return index is used as the variable for returns, for which the formula is displayed below:

$$R_t = R_{t-1} \times \frac{P_t + A_t + NC_t + CP_t}{P_{t-1} + A_{t-1} + NC_{t-1}}$$

Where R = total returns

P = price of the bond

A = accrued interest

NC = next coupon

CP = value of any coupon received on t or since t-1.

Credit spread is derived straight from Refinitiv Datastream and implies in this case the difference in yield of a corporate bond compared to a government bond of the same maturity. The yield spread is calculated by matching the corporate bond yield to a calculated government bond yield using constant maturity yields published in the Financial Times. Yield to maturity is the total yield of the bond if it is held to maturity. Modified duration is a measure of the sensitivity of a bond's price to the changes in yield. Time to maturity is simply the runtime the bond has left, measured in years.

In the study we are mainly interested in the excess returns of the factor investing strategies. Therefore, we also need to consider the risk-free interest rate and a benchmark index for the bonds. As the risk-free interest rate, we use the 3-month maturity yield curve spot rate of triple A rated government bonds in the euro area. The data is provided by the European Central bank and available on their website. In the beginning of the period the risk-free rate was above 0, but since 2015, it has been negative. This affects the calculated excess returns as deducting negative rates increases the bonds' calculated returns. Bloomberg Barclays Euro Corporate Bond Index is used as the benchmark index. The index aims to track the performance of fixed-rate, investment-grade Euro-nominated corporate bonds.

Using the benchmark index, it is possible to determine whether the tested factor strategies produce alpha and to study for example if the Sharpe ratios calculated for the portfolios are significant when compared to the index. The usage of Euro-nominated corporate bond index is not most ideal as it obviously includes bonds from several countries that are not Nordic, but as a benchmark index for purely Nordic corporate bonds does not exist, the former has to be used. Also, as discussed below, the dataset and the benchmark index track each other rather closely.

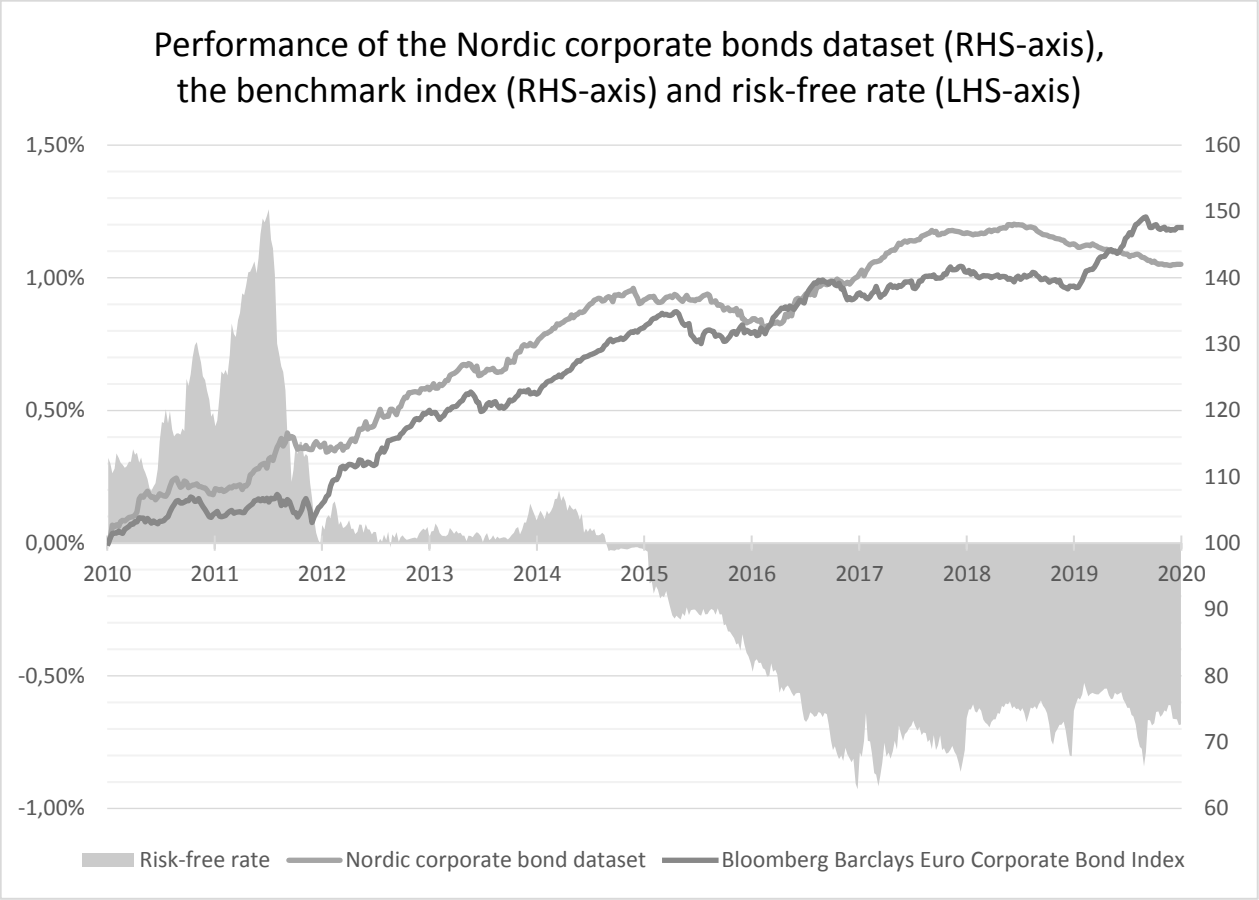

Figure 5. The performance of the Nordic corporate bonds dataset, the benchmark index and risk-free rate

In the figure 5 above, we can see the change in both the Nordic corporate bonds that are included in the dataset as well as the benchmark index (Y-axis on right side) in the period of 2010 - 2020. As said, it should be noted that the time series follow each other rather closely. For most of the period the dataset has performed better than the index although in the last year the benchmark has a much stronger performance. Both of the indexes performed strongest over the period from 2012 to the beginning of 2015, when both indexes increased substantially and made approximately half of their total gains. The risk-free rate's changes are also shown in the figure (Y-axis on left side). In the beginning of the observation period the rate environment was closer to the so called old normal and the rates were clearly above zero, before dipping close to zero in the beginning of 2012. After the year 2015 the rates have decreased to negative and have kept down for the remainder of the observation period.

Table 1. Descriptive statistics

	Mean	Std.	Skewness	Kurtosis
Annualized excess return (Nordic bond dataset)	4,81 %	3,34 %	-0,60	-0,07
Annualized excess return (Benchmark index)	4,90 %	3,44 %	-0,645	0,0040
Time to maturity (years)	7,52	9,40	0,13	-1,31
Credit spread (bps)	235	157	0,38	-0,25
Duration	5,92	6,36	0,03	-1,24
Carry	5,54 %	17,60	1,20	1,29

The descriptive statistics for the dataset can be seen in Table 1. The annualized excess returns as well as the other statistics for both the Nordic bonds dataset and the benchmark index are relatively similar, which is not a surprise as the dataset tracks the index rather closely and vice versa. The maturities of the bonds are relatively long as the average time to maturity is over seven years. Credit spread is about 2% on average although the standard deviation for it is a bit high. This is also the case for carry for which the standard deviation is almost three times the mean of 5,54%.

4.1 Methodology

The methodology used in the empirical study will follow the examples of studies done before by other academics. Specifically, the approach used by Houweling and Van Zundert (2017) and Jegadeesh and Titman (1993), also explained well by Gebhardt et al. (2005), is adopted. Their method was to divide the bonds into equally weighted top and bottom portfolios with highest or lowest exposure to the specific factor. For example, bonds with the highest (lowest) past 6 month returns (measure of momentum) belong to the highest (lowest) decile portfolio. The portfolios are balanced every 6 months to achieve realistic results and to prevent overly high turnover. To avoid bid-ask bounce

and short term price reversal, one month period is skipped between the formation and holding periods like done by Jostova et al. (2013) and in other literature.

After the portfolio returns are calculated, they are compared with Sharpe ratio to adjust the performance for risk. The statistical significance of the Sharpe ratio is tested by determining if the portfolio's ratio is different from the ratio of the corporate bond market according to the method developed by Jobson and Korkie (1981), later refined by Memmel (2003).

The outperformance statistics are then studied for the portfolios. Firstly, the simple outperformance against the index is calculated, and tested if it is different from zero with t-test. Tracking error and information ratio are also displayed. These two statistics were discussed more specifically in subsections 1.4.3 and 1.4.4. Multifactor portfolios are constructed by investing equal proportions in every factor portfolio like previously explained.

In addition, we control for systematic risk of the factor portfolios by regressing their returns on the risk-premium of the corporate bond market. This way we can derive the possible CAPM alpha as the risk premium cannot explain away the alpha of the portfolio returns that the factor produces. All of the regressions in the thesis are ran with the Newey-West standard error corrections to account for possible autocorrelation and heteroskedasticity. The first regression equation can be seen below:

$$R_t = \alpha + \beta R_{mt} + \varepsilon_t$$

Where R_t = excess return of factor portfolio

α = CAPM-alpha

R_m = corporate bond market premium (benchmark index excess returns)

ε_t = error term

Lastly, the systematic risk is corrected by regressing the factor portfolio results with the risk factors Fung and Hsieh (2001; 2004) used, the Fama-French (2015) five factor model factors, their equity momentum factor and the corporate bond market premium.

Because the mentioned factors are only available in monthly time series the portfolio time series were transformed into monthly series as well. The idea behind the regression analysis is to correct for systematic risk but the analysis will also present the possible connection between the regressor factors. (Lin et al. 2017; Houweling & Van Zundert 2017; Bektic et al. 2018) The regression equation is as follows:

$$R_t = \alpha + \beta_1 PTFSBD_t + \beta_2 PTFSIR_t + \beta_3 DGS10_t + \beta_4 SP_t + \beta_5 MKT_t + \beta_6 SMB_t + \beta_7 HML_t + \beta_8 RMW_t + \beta_9 CMA_t + \beta_{10} MOME_t + \beta_{11} R_m + \varepsilon_t$$

Where $PTFSBD_t$ = Return of PTFS Bond lookback straddle

$PTFSIR_t$ = Return of PTFS Short Term Interest Rate lookback straddle

$DGS10_t$ = Monthly change in the 10-year treasury constant maturity yield

SP_t = Monthly change in the Moody's Baa yield - 10-year treasury constant maturity yield

MKT_t = Equity market premium

SMB_t = Equity size premium (small minus big)

HML_t = Equity value premium (high minus low)

RMW_t = Equity profitability premium (robust minus weak)

CMA_t = Equity investment premium (conservative minus aggressive)

$MOME_t$ = Equity momentum premium

The first four variables are inspired by Fung and Hsieh (2001; 2004) and the next six by Fama and French (2015). Variables PTFSBD and PTFSIR follow the returns of primitive trend-following strategy, which attempts to capture the maximum payout during a period by constructing a portfolio of look back options. Look back option is a type of exotic derivative that gives the owner the right to exercise the option at the most beneficial price of the underlying asset during the period before the expiration date. The variable PTFSBD is of bonds and the PTFSIR of interest rates. The next two variables,

DGS10 and SP, are significant return drivers in fixed income arbitrage funds (Fung & Hsieh 2004).

The Fung's and Hsieh's and Fama's and French's factors were downloaded from their respective sites. The Moody's Baa yield and 10-year treasury yield were obtained from the Federal Reserve Bank of St. Louis website.

5. Results

This section consists of the results of analyzing the different factor portfolios with the methods explained in the methodology chapter and reviewing the results. The return statistics are shown first, outperformance statistics second, CAPM-regressions results third and the multifactor regression results fourth. After these the multifactor portfolios are analyzed in the same manner. The results produced in the thesis are also compared to the results shown in the literature review.

5.1 Return statistics

The first part of the empirical study was to calculate the time series returns for each of the factor portfolios. As described before, the bonds were sorted by their factor scores to portfolios in the beginning of the periods, after which the returns of the portfolios were calculated. Table 2 displays the excess returns, volatility, Sharpe ratio and skewness and kurtosis adjusted Sharpe ratio for each of the portfolios. The statistics were calculated for the portfolios that should have the best performance as predicted in the hypothesis, but also for the portfolios that should have a worse performance according to it. This allows to examine if there is difference between the portfolios that might be related to the sorting principle.

Table 2. Return statistics for factor portfolios

Return statistics		Excess return	Volatility	Sharpe ratio	SKASR
	Index	4,93 %	3,44 %	1,44	1,28
Momentum	High	5,38 %	3,40 %	1,58	1,40
	Low	4,51 %	3,63 %	1,24	1,13
Maturity	Short	5,02 %	3,50 %	1,43	1,23
	Long	5,60 %	3,47 %	**1,61***	1,45
Volatility	Low	5,00 %	3,51 %	1,43	1,23
	High	5,34 %	3,68 %	1,45	1,29
Credit spread	Decreasing	4,88 %	3,58 %	1,36	1,21
	Increasing	5,23 %	3,75 %	1,39	1,20
Carry	High	5,72 %	3,38 %	**1,69*****	1,55
	Low	4,75 %	3,49 %	**1,36***	1,16
Average		5,14 %	3,54 %	1,41	1,29
Median		5,12 %	3,50 %	1,43	1,23

In the second upmost rows of the table, after the benchmark index' statistics, we have the momentum portfolio's returns. As anticipated, the excess returns of the high momentum portfolio beat the ones of low momentum portfolio by a margin of approximately 0,90%. The margin in returns is not particularly wide, but as the volatility for the high momentum portfolio is lower, the Sharpe ratio (1,58) compared to the low portfolio's one (1,24) is higher by a larger margin proportionally. The Sharpe ratios are not significant when compared to the index, but the high momentum portfolio's ratio beats the one of the index. This is also the case with the skewness and kurtosis adjusted Sharpe ratio. When comparing to the results in the literature, this thesis returns are more or less on the same level. For example Pospisil & Zhang (2010) achieved annual returns of approximately 5,6% with standard deviation of 2,79% which are roughly on the same level as the results above.

The low-risk portfolio measured by short maturity has excess returns of 5,02% and volatility of 3,50%. This causes its Sharpe ratio to be 1,43 and SKASR of 1,23. The

long maturity bonds have a nice return of 5,60% beating both the average return of the factor portfolios (5,14%) and the median return (5,12%). The Sharpe ratio for the portfolio is a bit surprisingly the second highest of all (1,61) as the volatility for the portfolio is 3,47%. The short-maturity portfolio's Sharpe ratio is not significant while the long maturity portfolio's ratio is significant on a 0,10 level. It should also be noted that the volatilities of the portfolios are practically on the same level, although the long maturity portfolio has a slightly lower one. This would indicate that, at least in terms of the volatility of the returns, there is not much difference in risk when comparing short and long maturity bonds. This in turn would mean that the metric is not adequate to measure risk and the time to maturity could be a proxy for another factor. When thinking of the reasons why long maturity bonds performed so well, one important one is the development of interest rates in the economy. As long maturity bonds are more sensitive to interest rate changes ie. have a greater duration, the declining rates have had a much more positive impact on long maturity bonds than in the short maturity ones. This for sure had a significant impact on the returns in the studied period as the rates trended lower for the majority of it. It is of course also a common precept that the longer maturity bonds should have a higher return as the risk is also higher. In any case, the time to maturity does not seem to measure risk that well at least in the light of these results and it could be more preferably used to measure some other factor. This of course does not mean that the metric in itself would be less useful as it produces good results.

When looking at the volatility factor portfolios the results are a bit lackluster. The returns are average compared to other factors and there is not much difference between the low and high volatility portfolios. Even the Sharpe ratios are similar with each other, the averages and the index portfolio's. Also, as the ratios are statistically insignificant, we can conclude that at least at this stage volatility as a measure is not particularly interesting. This is in line with the literature where volatility of the bond returns has not been found to be a particularly good factor in the corporate bond markets. On the other hand, this is in contrast to equity markets where low-volatility anomaly has been evidenced to exist (eg. Dutt & Humphery-Jenner, 2013; Baker, Bradley & Wurgler,

2011). Furthermore, the past volatility seems to predict the volatility in the future just a little bit as the low volatility portfolio indeed has a lower measured volatility of returns. However, it is not much lower than the average.

The case with the value factor, which is measured by the decreasing or increasing credit spread, is quite the same as for the volatility portfolios. The returns of either portfolios do not deviate that much from each other and the volatilities are also similar. Consequently, the Sharpe ratios and SKASRs are almost equal with no statistical significance. Therefore, it seems that using just the credit spread movement is not enough to achieve abnormal returns. In the literature the value factors are usually built from several variables (eg. Israel et. al 2018; Houweling & Van Zundert 2017) and it appears that this may be vital to make the factor work.

The last of the single factor portfolios, carry, provides us more interesting results. The high-carry portfolio has higher returns (5,72%) compared to the low-carry portfolio, as expected. The former portfolio returns are in fact the highest among all portfolios. The high carry portfolio also has the second lowest volatility which causes its Sharpe ratio to be the highest of all, being 1,69. The low carry portfolio has below-median and -average excess returns and Sharpe ratio, which again highlights the effect high carry has on the returns. The high-carry portfolio's Sharpe ratio is significantly higher than that of the benchmark portfolio, while the low-carry portfolio's is significant at the 1% level. In comparison to the results of Israel et al. (2018), these figures are on a slightly higher level in terms of return as their high-carry portfolio had returns of 3,7% annually with much higher volatility of 13,9%. On the other hand (Martens et al. 2017) long/short carry portfolio had an annual return of only 0,48% across all countries they investigated while the standard deviation was 0,24%. In the light of these results, bond carry as a factor seems to work really well in the Nordic markets.

When looking at the results as a whole we can see that the single factor portfolios long maturity and carry had the most success as their Sharpe ratios were significantly better that of the benchmark portfolio. The high momentum factor is also promising, though the results were not statistically significant. If one winner in this analysis had to be

chosen it would be the carry factor for sure. Its returns were the highest while its volatility was also low, which is the best of both worlds as usually the volatility (risk) increases with higher returns. As Ilmanen et al. (2004) put it: “For investors who can leverage up their risk exposures, raw returns are not as important as risk-adjusted returns. Thus, the smoothness of the cumulative gains matters at least as much as absolute extent of gains.” In other words, as investors can lever up their positions the risk-adjusted returns matter more than purely the size of returns. Surprisingly, the long maturity bonds also generated a good performance statistics. On the other hand, the value factor was a disappointment as no substantial difference between the decreasing and increasing spread portfolios was found. The results also go against the hypothesis as the decreasing credit spread bonds should perform better.

5.2 Outperformance statistics

The next step in evaluating the factor portfolios is to review the outperformance statistics displayed in Table 3. The first column shows simply the percentage points by which the portfolio has outperformed the benchmark index. To ensure that the values are different from zero, t-test is ran for every portfolio, with the t-values on display. The tracking error values are annualized by multiplying the weekly values with square root of 52. The information ratio is the result of dividing the outperformance returns by the tracking error.

Table 3. Outperformance statistics

Outperformance statistics		Outperformance	Tracking error	Modified IR	T-value
Momentum	High	0,45 %	3,50 %	0,13	**1,69***
	Low	-0,42 %	3,91 %	-0,016	1,39
Maturity	Short	0,08 %	3,04 %	0,03	0,37
	Long	0,67 %	3,85 %	0,17	**2,27****
Volatility	Low	0,07 %	3,75 %	0,02	0,24
	High	0,41 %	4,26 %	0,10	1,28
Credit spread	Decreasing	-0,05 %	4,46 %	-0,002	0,13
	Increasing	0,30 %	4,46 %	0,07	0,90
Carry	High	0,79 %	3,96 %	0,20	**2,59*****
	Low	-0,18 %	3,16 %	-0,006	0,76
Average		0,21 %	3,83 %	0,07	
Median		0,19 %	3,88 %	0,05	

The percentual outperformances against the benchmark index range from -0,42% to 0,79% with the average being 0,21% and median 0,19%. The best performers in pure excess returns are high carry, long maturity and high momentum portfolios as discussed in the previously. The excess returns for these three portfolios are also different from zero with confidence levels of 0,99, 0,95 and 0,9, respectively, whereas the excess returns for other portfolios do not show statistical significance in terms of t-statistics.

Like explained in 1.4.3, the lower the tracking error is, the more accurately the portfolio follows the benchmark. A low tracking error can be considered either good or bad thing depending on the context of evaluation. If the portfolio has a high alpha and high tracking error, we can consider it to be good but if the tracking error is high, but the alpha is low the performance is poor. In regard to the factor portfolios, the three lowest tracking errors belong, from smallest to largest, to the short maturity, low carry and high momentum portfolios. On the other hand, the largest tracking errors belong to the high volatility and the credit spread portfolios.

The modified information ratio is also calculated for each of the portfolios. The similar theme as in previous results holds for the information ratios as well: the highest ratios belong to high-carry, long-maturity and high-momentum portfolios. Low-momentum, low-carry and decreasing credit spread portfolios have the lowest ratios. The modified information ratio takes into account the negative excess returns and is advised to be used by Israelsen (2005).

5.3 Regression analysis (CAPM alpha)

In this section the results of the first regression analysis are reviewed. Table 4 shows the annualized alphas, betas and R-squared for every factor portfolio. The t-stats are disclosed only for alphas, as all the beta coefficients were very highly significant with t-stats above 20 in all cases. The standard errors are in the parenthesis.

Table 4. CAPM-regression statistics

CAPM-regressions		Alpha (annualized)	Beta	T-value	R-squared
Momentum	High	**4,71%*** **	0,87	3,30	0,77
		(0,014)	(0,024)		
	Low	0,20 %	0,91	0,14	0,74
		(0,014)	(0,024)		
Maturity	Short	1,89 %	0,93	1,48	0,83
		(0,013)	(0,023)		
	Long	**5,75%*** **	0,87	3,59	0,73
		(0,016)	(0,027)		
Volatility	Low	**2,78%***	0,88	1,80	0,75
		(0,015)	(0,024)		
	High	**3,96 %** **	0,90	2,24	0,70
		(0,017)	(0,030)		
Credit spread	Decreasing	**3,07%***	0,84	1,67	0,66
		(0,018)	(0,031)		
	Increasing	**3,39%***	0,9	1,74	0,68
		(0,019)	(0,034)		
Carry	High	**7,02%*** **	0,83	4,31	0,71
		(0,016)	(0,03)		
	Low	0,98 %	0,92	0,71	0,81
		(0,014)	(0,025)		

When the factor portfolios' excess returns are regressed with the excess returns of the benchmark index, we see some interesting results. Whereas the high momentum portfolio did not have a statistically significant Sharpe ratio, its alpha is highly significant with t-stat of 3,30. Furthermore, the annualized alpha is high, being 4,71%. When we compare the high-momentum portfolio to the low-momentum one, we can see a clear difference in performance, as the low-momentum portfolio's alpha is much lower with no statistical significance. These results would indicate that high momentum is a useful metric when predicting bond portfolio returns. The high-momentum portfolio also has a beta of 0,87 which is lower than the low momentum's one signaling lower risk.

The results for maturity portfolios are also interesting. The bonds that have long maturity show a highly statistically significant annualized alpha of 5,75%. This goes against the original hypothesis that the lower risk of short maturity bonds would yield

higher returns. The regression results support the earlier statistics where the long maturity portfolio was found to have a high and statistically significant Sharpe ratio. The short maturity portfolio yields no significant results but offers contrast showing the difference between the two metrics. Interestingly, the beta of long maturity bonds is lower than that of the short maturity bonds, thereby indicating that the hypothesis of short maturity bonds being less risky does not seem to hold at least in this dataset and period.

The portfolios sorted by the volatility of the returns show curious results in the context of regression analysis. Both of the volatility portfolio alphas are statistically significant at the better than 10% level, which was not the case for their corresponding Sharpe ratios. The high volatility portfolio also has the fourth highest alpha among all portfolios. The betas do not differ from each other that much, indicating either that there is not much difference in the riskiness between the portfolios. These results suggest, again, that volatility does not work as risk measure at least in light of the analysis with this dataset. However, it is possible that the time frame of the volatility (6 months) is not adequate, and the results could improve with a different timeframe. However, considering the lack of evidence in the research field on this metric working, it is more unlikely that the timeframe is the reason for this finding.

The value portfolio measured by decreasing credit spread does neither show especially good performance in the regression analysis. The alpha is actually higher for the increasing spread portfolio which is in contrast with the original hypothesis. It is also weakly significant at the 10% level. The results show that as discussed in connection with the return statistics, the decreasing credit spread is not a good predictive factor in the bond markets at least according to these results. The same argument about the timeframe could also be made here that was made for the measurement of volatility. In this case, the matter is not that straightforward as the research showed that specifically the three month improvement of the spread was a predictor of ratings change. A counterargument could be that as all bonds in the dataset do not have a rating the effect that the factor aims to detect is too weak or non-existent. This could very well be the case, though it is still possible that the credit spread decrease would make the bond

a more desirable investment and the rating change is just a proxy, or side effect, of this. Also, as mentioned earlier, even though the bonds and issuers do not necessarily have ratings given by official rating agencies such as S&P or Moody, the bonds and issuers are followed and analyzed by several other market participants.

The carry factor was the best single factor according to the return statistics and the case is same with the regression analysis too. The alpha for the high carry portfolio is very high, 7,02%, with high statistical significance. Meanwhile, its beta is the lowest of all the portfolios which implies that the risk level when compared to the market is not high either. This supports the earlier findings as the said portfolio had the highest risk-adjusted returns measured with Sharpe ratio as well. When we consider that the low carry portfolio's alpha is statistically insignificant and only a seventh of the high carry's alpha, the difference emphasizes the quality of the latter portfolio. We can already at this stage conclude that the high carry works really well as a long bond portfolio selection criterion.

In addition to the earlier results, the CAPM alphas and other results derived from the regression analysis give encouraging evidence that some of the factors analyzed can function well in practice. In this analysis, high-momentum, long-maturity and high-carry portfolios performed the best. What was also encouraging is that the results of the return statistics supported the results of the regression analysis.

5.4 Multifactor regression results

This section will review the results of the multifactor regression analysis described in the methodology chapter. As analyzing all of the factor portfolios would produce unnecessary clutter, only the five most successful portfolios are analyzed. These are the high-momentum, long-maturity, high-carry, low-volatility and decreasing credit spread portfolios. The last two portfolios were not the clear winners within their category, but they are in accordance with the original hypothesis that is being studied and were chosen to be analyzed because of that.

Table 5. Results of the multifactor regressions

Multifactor regression	Momentum	Low-risk (Maturity)	Low-risk (Volatility)	Value	Carry
Alpha (annualized)	**4,44%*** **	4,63 %	2,27 %	2,14 %	**5,62%*** **
	(2,94)	(1,50)	(0,7)	(0,61)	(2,87)
PTFSBD	0,003	-0,002	0,009	0,00	-0,01
	(0,47)	(-0,420)	(1,19)	(-0,01)	(-1,20)
PTFSIR	0,004	0,012	0,010	0,00	0,0111
	(0,64)	(1,16)	(1,09)	(0,43)	(1,27)
DGS10	0,015	-0,0002	0,031	-0,0194	0,0174
	(0,43)	(-0,01)	(0,57)	(-0,37)	(0,43)
Spread	0,035	-0,018	0,005	-0,02	0,00407
	(0,69)	(-0,29)	(0,06)	(-0,23)	(0,07)
MKT	**-0,100*** **	**-0,085*** **	**-0,111*** **	**-0,123*** **	**-0,063*** **
	(-4,26)	(-3,00)	(-2,74)	(-3,79)	(-2,69)
SMB	0,091	0,184	0,1	0,08	**0,22680** **
	(1,07)	(1,45)	(0,86)	(0,59)	(2,20)
HML	0,096	0,494	**0,218***	**0,244***	0,0904
	(1,30)	(0,45)	(1,70)	(1,74)	(0,80)
RMW	0,141	0,181	0,26	0,21	0,16014
	(1,52)	(0,98)	(1,35)	(0,94)	(1,20)
CMA	0,171	0,278	0,12	0,08	**0,289***
	(1,16)	(1,24)	(0,59)	(0,35)	(1,78)
MOME	-0,025	0,031	0,01	0,05	0,04
	(-0,61)	(0,36)	(0,12)	(0,57)	(0,87)
Benchmark index	**0,936*** **	**0,945*** **	**0,96*** **	**0,904*** **	**0,910*** **
	(42,97)	(36,50)	(36,20)	(24,44)	(36,35)
Adj. R-Squared	0,94	0,92	0,93	0,88	0,93

The results of the multifactor regressions are shown in Table 5. The uppermost row is dedicated for the annualized alphas for each of the portfolios. The rows for other independent variables show the corresponding coefficients. The t-stats are in the

parenthesis below each regression coefficient. Also, the adjusted R-squares are disclosed.

The standout result is that two of the portfolios produce highly significant alpha even after controlling for several market risk premiums. As previous results have shown, the best portfolio is the high carry one, which has 5,62% annualized alpha in this regression analysis. The high momentum portfolio follows suit with 4,44%. The low-maturity and value portfolios do not produce a significant alpha. The fact that the long-maturity portfolios alpha (4,63%) is insignificant is a bit unexpected, as it was highly significant in the earlier analysis. However, this makes sense when one takes into consideration the original hypothesis which predicted that the short maturity, not long maturity ones would produce better returns.

When taking a look at the explanatory variables, it can be seen that only five of them are significant in the five different regressions. The equity market risk premium is significant in every regression with a negative coefficient. The equity size factor is significant in the carry regression, the equity value factor in the low volatility and value regressions, the equity investment factor in the carry regression and, as in the earlier analysis, the bond market index is significant in every regression. It should be noted that none of the variables suggested by Fung and Hsieh (2001; 2004), nor the equity profitability and momentum factors are significant in the regressions.

5.5 Results for multifactor portfolios

The multifactor portfolios are assembled on the basis of the single-factor portfolio's success in the earlier analysis and on the basis of the original hypotheses. Altogether, three different portfolios are constructed, and the same analysis is performed on them as for the single-factor portfolios. The way the portfolios are assembled is shown in Table 6.

Table 6. Multifactor portfolios

Multifactor 1	High momentum	Short maturity	Decreasing spread	High carry
Multifactor 2	High momentum	Long maturity	High carry	
Multifactor 3	High momentum	High carry		

The first portfolio is built according to the original hypothesis which predicted that high-momentum, short-maturity, decreasing credit spread and high-carry factors would be most successful factors. The second portfolio is built on the basis of the CAPM regression results by selecting the most successful portfolios, and the third one on the multifactor regression results with the same principle. The portfolios invest equally in the single factor portfolios, so that in the first portfolio one single factor is a fourth of the portfolio, in the second one a third and in the third a half of the portfolio, respectively. The same results are calculated for the multifactor portfolios as for the single-factor portfolios in the earlier part of the thesis.

Table 7. Return statistics for multifactor portfolios

Return statistics	Excess return	Volatility	Sharpe ratio	SKASR
Index	4,93 %	3,44 %	1,44	1,280
Multifactor 1	5,25 %	3,32 %	**1,58***	1,418
Multifactor 2	5,57 %	3,33 %	**1,67*****	1,513
Multifactor 3	5,55 %	3,32 %	**1,67*****	1,510

The excess return of the first portfolio is 5,25% which beats the benchmark index as well as the average and median of all the single-factor portfolios. This holds because its volatility is also lower than the index'. This goes well along with the hypothesis as in theory diversification should lower the risk of the portfolio. The same also holds for the second and third portfolio. Both of their returns are very similar, the second one being marginally better. The volatilities for the portfolios are also almost identical even though one could imagine that the volatility should be lower when diversifying to more factors. The last two portfolios have also highly significant Sharpe ratios. In light of these results

the multifactor portfolios are a good alternative for single factor portfolios as they outperform every one of them except the high-carry portfolio. The result is interesting and is in line with the results of Israel et al. (2018) as their combo portfolio also outperformed the single-factor portfolios.

Table 8. Outperformance statistics for multifactor portfolios

Outperformance statistics	Outperformance	Tracking error	Information ratio	T-value
Multifactor 1	0,32 %	3,17 %	0,102	1,32
Multifactor 2	0,64 %	3,42 %	0,187	**2,42****
Multifactor 3	0,62 %	3,45 %	0,180	**2,34****
Average	0,53 %	3,35 %	0,16	
Median	0,62 %	3,42 %	0,18	

The performance statistics show that the outperformance for the portfolios is significant for the second and third portfolio. The second portfolio has the highest margin of outperformance compared to the benchmark but only with a small difference with the third portfolio. The lowest tracking error belongs to the first portfolio with a value of 3,17%. Again, the values for the second and third portfolio are very similar. The same also holds in terms of the information ratio, as it is the lowest for the first portfolio followed by the two other combination portfolios with a small margin between each other. When comparing the results to the single portfolio ones, we can notice that on average the outperformance is more evident for the multifactor portfolios. The tracking error is higher for the single-factor portfolios on average, whereas the information ratio is higher for the multifactor ones.

Table 9. CAPM regression results for multifactor portfolios

CAPM regressions	Alpha (annualized)	Beta	T-value	R-squared
Multifactor 1	**4,15%*** **	0,87	3,25	0,81
	(0,013)	(0,022)		
Multifactor 2	**5,82%*** **	0,86	4,12	0,78
	(0,014)	(0,02)		
Multifactor 3	**5,86%*** **	0,85	4,18	0,78
	(0,014)	(0,02)		

The first multifactor portfolio has a rather good performance with highly significant alpha of 4,15%. Compared to the earlier analysis, the results are a bit weaker as some single -factor portfolios have higher alphas. The second and third portfolio produce higher alphas with values of 5,82% and 5,86%. These are great results and beat every single-factor portfolio except the high-carry one which had an outstanding alpha of 6,92%. The goodness of the high-carry portfolio is also shown by its beta being lower than all of the multifactor portfolios' ones. In any case, assembling multifactor portfolios can be worthwhile as they still produce better results than almost all of the single-factor portfolios. The CAPM betas of the multifactor portfolios do not basically differentiate from each other (only a 0,02 difference between portfolios 1 and 3), implying that the results of the regressions parallel the return statistics where the volatilities did not considerably change when less factors were in the portfolios.

Table 10. Results of the multifactor regression of multifactor portfolios

Multifactor regression	Multifactor 1	Multifactor 2	Multifactor 3
Alpha (annualized)	3,18 %	**4,89%****	**5,03%*****
	1,58	2,45	3,15
PTFSBD	0,000	-0,003	-0,003
	-0,08	-0,42	-0,39
PTFSIR	0,004	0,009	0,008
	0,59	1,15	1,1
DGS10	0,018	0,011	0,016
	0,55	0,3	0,45
Spread	0,022	0,007	0,020
	0,45	0,13	0,38
MKT	**-0,097*****	**-0,082*****	**-0,081*****
	-4,47	-3,6	-3,63
SMB	0,098	**0,167***	**0,159***
	1,19	1,68	1,77
HML	0,140	0,079	0,093
	1,65	0,88	1,22
RMW	0,154	0,161	0,150
	1,25	1,29	1,46
CMA	0,166	0,246	0,230
	1,08	1,45	1,53
MOME	0,027	0,016	0,008
	0,51	0,3	0,2
Benchmark index	**0,936*****	**0,930*****	**0,923*****
	41,23	41,63	42,12
Adj. R-Squared	0,94	0,95	0,95

The regressions with multiple factor premium variables follow the corresponding results of single factor regressions as well. The only significant variables trough the regressions are the equity market risk premium, equity size premium and the benchmark index. As for the single factor portfolios, the variables PTFSBD, PTFSIR, DGS10 and Spread were not significant in any regression. The RMW and MOME factors were also statistically insignificant.

However, the results show that even when controlled with several risk premia, the multifactor portfolios generate significant alpha, except for the first portfolio. The alphas values are lower than in the earlier regression analysis but still, the second portfolio has an alpha of 4,89% and the third portfolio of 5,03% which are both rather high and again, beat all of the single-factor portfolios' alphas, except that of the high carry one. Also, a small difference between the multifactor regressions and the other results is that the margin between the returns of portfolios 2 and 3 is a slightly wider, although still marginal.

6. Discussion and conclusions

This thesis examined the performance of different factors in the Nordic corporate bond market. The factors to be studied were chosen on the basis of the formerly done research, and were based on value, low risk, momentum and carry. Also, the proxies that the factors were measured with were supported by the earlier literature. The success of the factor portfolios was measured with several performance measures, including excess returns, the Sharpe ratio, SKASR and alpha controlled with the bond market risk premia and with various different risk factors.

The main research question and the first sub-question of the thesis were:

- Is it possible to achieve abnormal returns in Nordic corporate bond markets with the use of different factors?
- Which factors perform the best or worst?

Judging purely with the results in this thesis, the answer to the main question would be that it is indeed possible to achieve abnormal returns by practicing factor investing in the Nordic corporate bond markets.

When looking how the individual factors performed, the clear winner is the carry factor, which outperformed all other single factor portfolios as well as the multifactor portfolios while having a relatively low volatility. This combination of risk and return is of course what every investor and portfolio manager should be looking for. The second and third best factor portfolios were the ones based on a high momentum and a bit surprisingly, on long maturity. Momentum as a factor has been studied extensively in bond markets but especially in the equity markets and is a well evidenced phenomenon. The success of the long maturity portfolio is less supported by the literature. One possible reason for its good performance could be that usually only well established, reliable and trusted companies can issue long maturity bonds. This signal effect of long maturity could then affect the returns.

What the results also showed is that the low-risk proxy of shorter time-to-maturity is not particularly effective at least when examining this dataset. In addition, the value factor measured with changing credit spread and the low-risk factor measured with volatility did not have a statistically significant effect on the returns. For volatility, this result was expectable as the earlier literature had not found evidence for it in the corporate bond markets, although it is well evidenced in the equity markets. For value factor, the problem could have been in the measure, as when measured with other variables it had been documented to exist.

The possibility to achieve abnormal returns is supported by the evidence presented in the literary review, based on which the factor investing may be a valid method to produce abnormal returns in other markets. In most cases the research was done with data from the US markets where the market is likely more efficient, and consequently, abnormal returns are harder to obtain.

However, when considering the real life constraints, it is hard to say whether the results obtained in this research would persevere. One would have to take into account the

liquidity of the bonds, transaction costs and other aspects that could affect the net returns of the portfolios.

The second and third sub-questions of the thesis were:

- How do multifactor portfolios perform?
- Which multifactor portfolio combination produces the best results?

All in all, multifactor portfolios performed well in comparison to the single-factor portfolios. A bit unexpectedly, the portfolios with more factors did not have a lower risk in terms of volatility. Multifactor portfolios two formed of high-momentum, long-maturity and high-carry factors and portfolio three formed of high-momentum and high-carry factors performed better than portfolio one formed of high-momentum, short-maturity, decreasing spread and high-carry factors and had more solid performance than all single factor portfolios except the carry portfolio. Choosing the better among the two best multifactor portfolios is hard as they have very similar yields and risk metrics, as well as similar risk/return relationships.

Managerial implications of these results would be that including style factors into the toolbox when making investment decisions and considering different investing options would be beneficial for example for portfolio managers or other investors. Managers could utilize the results by focusing their attention specifically on bonds that have high carry and momentum.

Possible further research recommendations could be to broaden the geographical area from Nordic countries to Europe or North America and to lengthen the sample period as more data of the bonds would be available. Of course, an obvious expansion would be to measure the factors with other proxies, for example by constructing them from several variables, or by using different time periods for momentum indicators.

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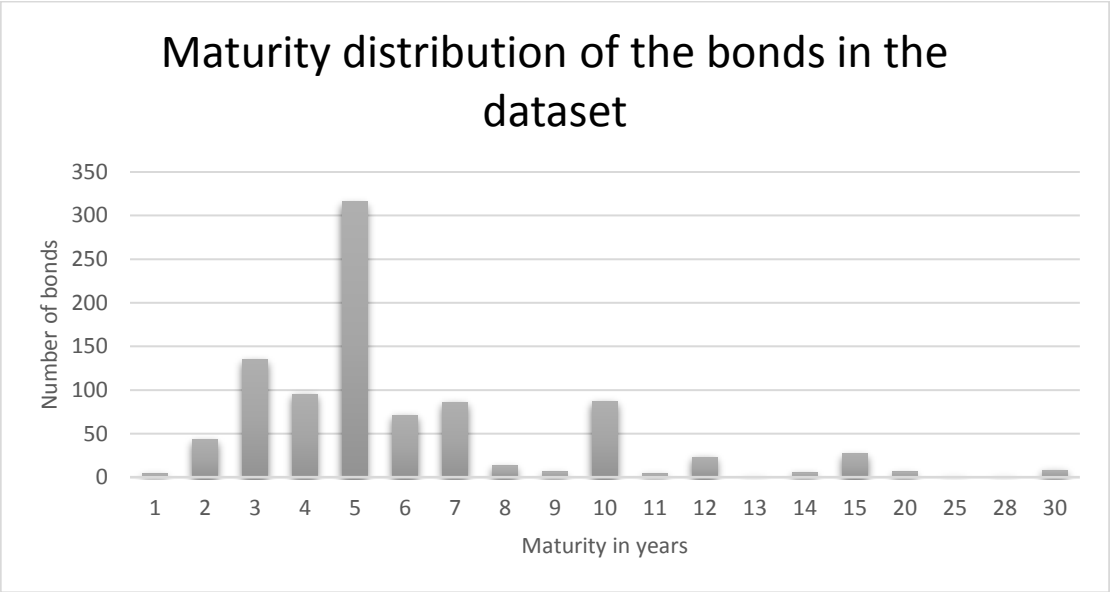
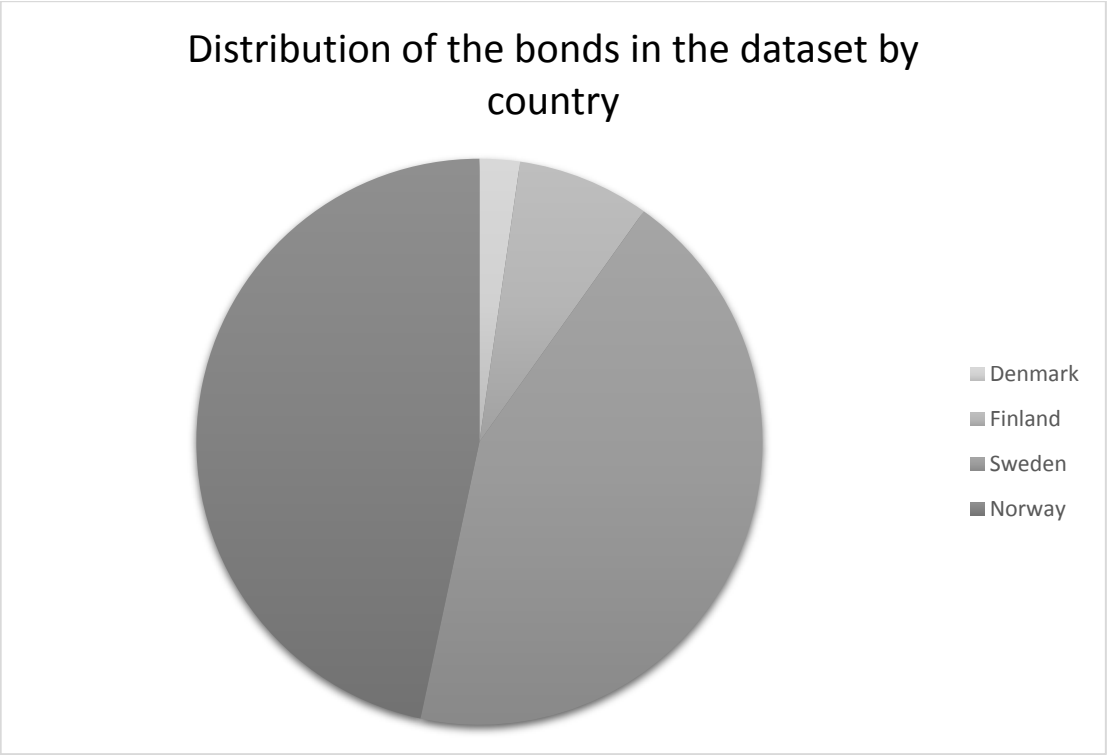
Appendices

Appendix 1. Maturity distribution of the bonds in the dataset



Appendix 2. Distribution of the bonds in the dataset by country



Appendix 3. Distribution of amount issued in the dataset by country