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Predicting Credit Spread Dynamics in the Norwegian Corporate Bond Market

An empirical analysis of High Yield and Investment Grade bonds in the Period 2014-2022

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Abstract

This thesis examines the credit spread dynamics between High Yield (HY) and Investment Grade (IG) bonds in the Norwegian corporate bond market. The sample consists of monthly pricing data for 37 distinct bonds spanning from 2014 to 2022.

We apply the extended Merton model (Eom et al., 2004) to calculate model credit spreads further used in the analysis. The first part of the analysis is a regression analysis comparing the mispricing between HY and IG bonds. Applying several non-default-related variables, we explore the differences in mispricing, both in terms of explanatory power and their relative magnitude. The second part of the analysis is a regression analysis aiming to predict credit spread differences between HY and IG.

We find that the model underpredicts credit spreads for HY but overpredicts credit spreads for IG. Furthermore, modelled credit spreads explain 3.1% of the variance in observed credit spreads for HY bonds and 1.9% for IG bonds. We identify that both risk grades are broadly affected by the same variables but with different magnitudes. HY appears to be more sensitive to industry dynamics and market risk compared to IG. Lastly, leverage plays a pivotal role in explaining variance in credit spread differences, having an explanatory power of 83.6%.

Keywords – Corporate Bonds, Credit Spread, Merton, High Yield, Investment Grade

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1 Introduction

The bond market offers an alternative platform for issuing debt, known as the primary market. Additionally, one can buy and sell debt securities, such as bonds, on the secondary market. The Norwegian bond market is mostly an over-the-counter (OTC) market, relying on intermediary brokers. This makes market information less transparent, limiting data access. Restricted data access could possibly explain the limited extent of studies on the Norwegian bond market. In later years, the Norwegian High Yield (HY) bond market has grown to become an important international market. This can, in great part be attributed to lower regulatory requirements compared to other markets. In contrast, the Investment Grade (IG) bond market in Norway is still considered to be relatively small.

Most literature on corporate bonds is primarily focused on the US market. However, increasing interest in bond financing in the Norwegian and Nordic markets has led to the emergence of new and interesting literature. A common attribute is that they all use structural models.

Ytterdal and Knappskog (2015) investigates the Nordic HY market, exploring the credit spread component. Utilizing a structural model, they find that default risk accounts for 65% of the observed credit spread. They identify liquidity as a significant explanatory variable beyond default risk. Eskerud (2017) performs a study on the Norwegian corporate bond market, including both risk grades. He finds the structural model to, on average, overpredict credit spreads. Furthermore, he identifies that the model is sensitive to changes in recovery rate. Sæbø (2011) conducts a similar study on the Norwegian corporate bond market. On the contrary, he finds the model to underpredict credit spreads. He identifies variables such as industry and size to explain a great portion of the variance in credit spreads. Another interesting study on credit spread differences between Nordic and European HY by Berg (2022). He finds that default risk accounts for 60% of credit spreads in the Nordic HY market and 70% for European HY. In addition, he identifies various variables explaining 50% of variances in credit spread differences.

In existing literature, there is a gap in exploring credit spread dynamics in the Norwegian corporate bond market. Especially comparing the credit spread dynamics between HY and IG bonds. Recognizing this gap, we construct the following problem statement: "Predicting Credit Spread Dynamics in the Norwegian Corporate Bond Market".

This thesis has two main objectives. Firstly, to explain how non-default-related variables affect mispricing differences between HY and IG bonds. The focus extends to both their relative magnitude and explanatory power. Secondly, to predict the determinants of credit spread differences between HY and IG bonds and quantify their effects. This is beneficial for market participants in the fixed income realm, as it provides a better understanding of bond pricing dynamics between the risk grades.

We apply a data set from Nordic Bond Pricing (NBP) containing corporate bond data for the Norwegian bond market spanning from 2014 to 2022. We apply the extended Merton model, first introduced by Eom et al. (2004). It enables us to identify how much default risk contributes to the observed spread. Furthermore, our analysis is twofold. The first part contains a regression analysis comparing how non-default-related risks affect mispricing. The second part of the analysis contains a regression analysis predicting the determinants of credit spread differences between the risk grades.

Our main findings are that structural models tend to underpredict credit spreads for HY bonds but overpredict spreads for IG bonds. We identify industry and market risk as important variables in explaining the variance in mispricing for both risk grades. Additionally, leverage is an important variable in predicting credit spread differences between the two risk grades, explaining 83.6% of the variance.

The structure of this thesis is as follows: Chapter 2 presents a brief overview of bond theory, followed by a review of relevant literature emphasizing structural models in chapter 3. Chapter 4 describes our data processing, while chapter 5 describes our chosen methodology. Chapter 6 presents our analysis and discussions, while chapter 7 presents robustness tests of our findings. Finally, chapter 8 concludes with our findings, limitations, and suggestions for future research.

2 Basic Bond Theory

2.1 Bond Basics

A bond is a debt security where an issuer sells a bond to the public with a promise to pay back interest plus principal in the future. In doing so, the issuer receives capital upfront to fund investments and daily operations. The interest payment is also referred to as a coupon payment. A bond can be issued with or without a coupon payment. A bond with no coupon payments is also known as a zero-coupon bond. Coupon paying bonds can have a fixed or floating rate. The floating rate is comprised of a fixed rate plus a variable rate, which is often tied to the Norwegian Interbank Offered Rate (NIBOR). The yield is calculated through yield to maturity (YTM). It is the bond's internal rate of return at a given market price. The downside of YTM is that it assumes that the coupon payments are reinvested at the YTM rate. This assumption introduces reinvestment risk as one cannot be certain about future rates.

2.2 Type of Bonds

Bonds are differentiated by issuer type and bond characteristics. Private and public corporations, governments, and government entities are the most prominent issuers of bonds. Corporate bonds can be backed by collateral or the company's future earnings, with the latter being riskier. Contrary to corporate bonds, government bonds carry the full faith and credit of a government, making them safer (SEC, 2023). However, risk profiles and credit risk differ substantially between governments.

The bond indenture, which is the contract between issuer and bondholder, dictates the characteristics of the bond (Bodie et al., 2018, p. 452). Some bond types are callable, puttable, convertible, inverse floaters, and indexed bonds. A bond with a call option gives the issuer the option to buy back the bond at a given price prior to maturity. In a market with declining rates, a call option is valuable to the issuer because the company can refinance its debt at a lower interest rate. A puttable bond has the same characteristics as a callable bond, but this option applies to the bondholder. This is beneficial for the bondholder when the coupon rate is higher than the market rate. If the coupon rate is below the market rate, it is optimal to redeem the bond and claim the principal. For both option types, one's benefit is another's burden, which is reflected in the bond price.

Convertible bonds give the bondholder the option to convert a bond into a prespecified number of shares. Convertible bonds have upside potential in cases where the company's shares appreciate and converting becomes optimal. This means one can exceed the bond yield by converting to stocks. This benefit comes at a cost in the form of lower yields and coupon rates.

Inverse floaters are bonds with coupon rates that fluctuate inversely with the market rate. When market rates fall, the coupon rate increases. Increasing market rates consequently lead to a decreasing coupon rate. As a result, market rate fluctuations magnify the change in return of the inverse floater.

Indexed bonds make payments that are tied to a general price level index or a specific commodity price (Bodie et al., 2018, p. 431). Unlike a conventional bond that pays a fixed amount of principal, an indexed bond pays a principal that is adjusted for price levels (Neely, 1997). Hence, indexed bonds provide a return that is unaffected by inflation or commodity prices. Consequently, investors are interested in such security as it protects the real rate of return of an investment from unexpected changes in price levels.

2.3 Bond and Capital Structure

A company finances its assets in the balance sheet through a mixture of common equity, preferred equity, short-term debt, and long-term debt (Tuovila, 2023). In the event of default, debt has a higher priority than equity. Hence, the cost of equity is usually higher than the cost of debt (Vipond, 2023). Companies often have different debt securities with different priority levels. Senior secured with collateral being the highest ranked security on the balance sheet. Senior unsecured entails seniority over subordinates but does not have collateral. Subordinate debt is the lowest ranked debt but is still higher ranked than preferred and common equity. Equity is the lowest ranked security, with preferred equity having a higher priority than common equity.

2.4 Risk Categories

The creditworthiness of an issuer is determined through a credit risk assessment. This is usually done by rating agencies such as Moody's, Standard & Poor's (S&P), and Fitch. They assess the risk that an issuer might not fulfill the promised interest and principal payment (Fidelity, 2023). Based on the assessment, the issuer is assigned to a risk category, as shown in table 2.1. The risk category has two broad risk grades, called IG and HY.

IG refers to bonds rated Baa3/BBB- or better. These bonds are considered to carry lower default risk. As a result, risk compensation is lower. They are usually issued by stable companies and government entities, making them attractive to risk averse investors.

HY refers to bonds rated Ba1/BB+ and below. These bonds carry higher credit risk, and default is not uncommon in this segment. Almost half of all bonds rated triple-C by S&P have defaulted within 10 years (Bodie et al., 2018, p. 449). To compensate for the higher risk, as the name suggests, investors are rewarded with a higher yield.

Table 2.1: Credit Rating

	Moody's	S&P	Fitch
Investment Grade	Aaa	AAA	AAA
	Aa1	AA+	AA+
	Aa2	AA	AA
	Aa3	AA-	AA-
	A1	A+	A+
	A2	A	A
	A3	A-	A-
	Baa1	BBB+	BBB+
	Baa2	BBB	BBB
	Baa3	BBB-	BBB-
High Yield	Ba1	BB+	BB+
	Ba2	BB	BB
	Ba3	BB-	BB-
	B1	B+	B+
	B2	B	B
	B3	B-	B-
	Caa1	CCC+	CCC+
	Caa2	CCC	CCC
	Caa3	CCC-	CCC-
	Ca	CC	CC
	C	C	C
		D	D

This table presents the credit rating range from Moody's, S&P, and Fitch. The ratings are categorized into IG and HY (Fidelity, 2023).

2.5 Shadow Rating

In today's Norwegian market, a credit rating is necessary for a company to issue bonds. An official credit rating is often costly and time-consuming. Therefore, shadow rating was more viable and widely used by investors and experts prior to 2016. Shadow rating was an unofficial rating given to issuers without any public announcement (Hayes, 2022). It was performed by brokerage houses without any charge or fee from the issuer. Market participants in Norway used to accept shadow ratings as if they were official (Sønnervik, 2017). However, the European Securities and Markets Authority (ESMA) banned shadow ratings in 2016. This changed the feasibility of issuing new bonds as the official rating is costly. Nonetheless, from our data sample, we observe that a substantial number of issuers are still not officially rated.

Verdipapirfondenes forening (VFF) requires 70 percent of issuers in an IG fund to be officially rated. The ban further incentivizes existing IG issuers to have an official rating to be eligible for IG funds (Frafjord, 2020). As a result, new affordable rating companies have emerged in the Norwegian bond market.

2.6 Credit Spread

All corporate bonds carry default risk that is in accordance with the issuer's financial health. Hence, they carry a premium above a risk-free rate known as the credit spread. Bonds of highly stable governments, e.g., the US and Norway, are often used as a proxy for risk-free rates. Even government bonds are not immune to default risk but can serve as a reasonable proxy. Consequently, corporate bond yields above the risk-free rate with the same maturity must be compensation for added risk. This risk is the risk that the company may one day stop fulfilling its obligations to pay interest and principal.

Research has shown that the credit spread incorporates premiums that are beyond the default risk of the issuer. This is further discussed in section 3.5.

3 Literature

This chapter explores existing research and academic papers on the topic of credit pricing for corporate bonds. We aim to fill a gap in the literature, leading us to formulate the problem statement: "Predicting Credit Spread Dynamics in the Norwegian Corporate Bond Market". To the best of our knowledge, there are no studies that specifically examine a data set of corporate bonds in the Norwegian market. Specifically, with the aim of explaining how non-default-related variables affect mispricing differences. Including both their relative magnitude and explanatory power between HY and IG bonds. Additionally, previous research has not focused on predicting the credit spread difference between these two risk grades.

3.1 Credit Pricing

There are mainly two known models for traditional credit pricing, namely structural and reduced form models. Structural models are based on contingent claim valuation, first introduced by Black and Scholes (1973). It was Merton (1974) who first famously applied option pricing theory to corporate debt valuation, addressing credit risk. The works of Merton have since been widely acknowledged as a foundational element of structural models in credit pricing, essentially forming the basis for all subsequent structural models. Reduced form models, first introduced by Jarrow and Turnbull (1995), utilize historical time series data to estimate parameters. They treat credit defaults as an exogenous event driven by a stochastic process. These models heavily rely on historical data and are proven to have good in-sample fitting but limited out-of-sample predictive power. Furthermore, reduced form models are often criticized for their limited ability to provide economic insights into defaults, as these models treat defaults as purely statistical events.

Our chosen model for the analysis is an extended version of the original structural model by Merton, commonly referred to as the extended Merton model. This model, first introduced by Eom et al. (2004), allows for the valuation of coupon paying bonds. It treats a coupon paying bond as a portfolio of zero-coupon bonds. The details of this model will be thoroughly described in chapter 5.

There are several motivating factors for the choice of model. Firstly, as Wang

(2009) highlights, structural models offer the appealing feature of connecting underlying structural variables to credit risk, providing a clear economic explanation. Additionally, this model has been employed in other studies focusing on the Norwegian and Nordic corporate bond markets, allowing us to compare results. Furthermore, as the model has a strong theoretical foundation as well as our familiarity with contingent claim valuation, interpretation and implementation of the model are feasible.

3.2 Structural Models

This section introduces the basic Merton model and its underlying assumptions. In addition, we will explore various adaptations and extensions of the Merton model that have developed over time.

3.2.1 Basic Merton Model

The Merton model employs the Black-Scholes option pricing framework, treating a company's equity as a call option on its underlying assets. Merton utilized this relationship to price a company's debt under the no-arbitrage argument. Firstly, we present the principles and intuition behind option pricing theory as applied to equity and debt.

Equity can be regarded as a call option on the firm's assets, with the strike price equivalent to the face value of debt. The intuition is that if a firm's assets exceed its debt, equity holders are entitled to the residual value. Conversely, if the firm's assets are insufficient to cover its debt obligations, it faces insolvency. The equity holders are left with no residual value.

$$\text{Equity} = \text{Call Option(Face Value of Debt)} \tag{3.1}$$

Debt is comparable to a combination of risk-free debt and a written put option on the firm's assets, with the strike price equal to the face value of debt. If the firm's asset value falls short of the value of debt, the put option is in-the-money, leaving debt holders with the firm's assets. If the firm's assets exceed the strike price, the put becomes out-of-the-money. This leaves debt holders only receiving the required debt payment.

$$\text{Debt} = \text{Risk-free Debt} - \text{Put Option(Face Value of Debt)} \tag{3.2}$$

The Merton model operates under a set of "ideal conditions". They are a series of assumptions that provide the theoretical framework for the model. These assumptions are presented by Sundaresan (2013) as follows:

1. "There are no transaction costs, taxes, or problems with indivisibilities of assets."
2. "There are a sufficient number of investors with comparable wealth levels such that each investor believes that he can buy and sell as much of an asset as he wants at the market price."
3. "There exists an exchange market for borrowing and lending at the same rate of interest."
4. "Short sale of all assets, with full use of the proceeds, are allowed."
5. "Trading in assets takes place continuously in time."
6. "The Modigliani-Miller (MM) theorem that the value of the firm is invariant to its capital structure obtains."
7. "The term structure is flat and known with certainty; i.e., the price of a riskless discount bond that promises a payment of $1 at time T in the future is $P(t,T) = e^{-r(T-t)}$, where r is the (instantaneous) riskless rate of interest, the same for all time."
8. "The dynamics for the value of the firm, V, through time can be described by a diffusion- type stochastic process."

The assumptions create an idealized framework that is not reflective of real-world conditions. Merton acknowledges that the assumptions forming the perfect market assumption (1-4) can be relaxed. He further clarifies that the seventh assumption is primarily focused on default risk rather than interest rate risk. This is determined by relevant variables in the economy. Consequently, the model's key assumptions are number five, six, and eight.

The model assumes that the firm's asset value V follows a geometric Brownian motion

(GBM), shown by equation 3.3. The expected continuously compounded return on asset V is denoted by μ_V. The volatility of asset returns is presented by σ_V, and dW is the standard Wiener process. A standard Wiener process is a stochastic process that models random movements in continuous time. The framework of a Brownian motion suggests there are two components to the random movement of an asset. The first part is constant drift, illustrated by the first term. The second part is a random shock, represented by the second term. According to the central limit theorem, the random rate of an increase or decrease in the asset value implies that periodic returns are normally distributed. This assumption regarding the normality of returns is a fundamental element of the Black-Scholes model.

$$dV = \mu_V \cdot V \cdot dt + \sigma_V \cdot V \cdot dW \tag{3.3}$$

Merton (1974) applies the Black-Scholes formula to determine the value of equity as a call option on a firm's underlying assets, denoted by V. This option has maturity T and an exercise price equal to the face value of debt B. The formula for pricing a European call option is encapsulated in equation 3.4.

$$S = VN(d_1) - Be^{-rT}N(d_2) \tag{3.4}$$

where

$$d_1 = \frac{\ln\left(\frac{V}{B}\right) + \left(r + \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{3.5}$$

and

$$d_2 = d_1 - \sigma_V\sqrt{T} \tag{3.6}$$

The cumulative normal distribution function is denoted by $N(.)$, where r represents the continuously compounded risk-free interest rate. σ_V denotes the asset volatility.

Utilizing this framework, Merton (1974) values corporate debt. Debt can be expressed as the difference between a risk-free bond and a put option on V, with maturity T and exercise price B. This valuation, as presented in equation 3.7 uses the principles of option pricing to assess risky debt.

$$D = e^{-rT} B N(d_2) + V N(-d_1) \tag{3.7}$$

Alternatively

$$D = \underbrace{e^{-rT} B}_{1} - \left(\underbrace{e^{-rT} B - V \frac{N(-d_1)}{N(-d_2)}}_{2} \right) \underbrace{N(-d_2)}_{3} \tag{3.8}$$

Part 1 of the equation represents the value of comparable risk-free debt. Part 2 of the equation denotes the discounted expected loss given default. Lastly, part 3 expresses the likelihood of the asset value being below the strike price at maturity, consequently, the probability of the put option being exercised. This also represents the probability of default when valuing debt using options.

3.3 Extensions and Adaptations of the Merton Model

Empirical studies highlight key limitations of the Merton (1974) model. Especially its tendency to underestimate credit spreads. This is particularly true for short-term spreads on high-quality debt. Leading to the development of several adaptations and extensions addressing these shortcomings. One such adaptation is Black and Cox (1976) "first passage time model". This model allows for the possibility of default before maturity by incorporating safety covenants. Safety covenants allow creditors to take control of the borrowing firm if the value of the firm falls below a certain threshold. This introduces the element of uncertainty in default timing ex-ante. As a result, equity is no longer regarded as a European call option of the firm's assets but rather as a down-and-out call option.[1] Additionally, Black and Cox (1976) model extends to the valuation of senior and subordinated debt. Furthermore, they allow valuing coupon paying bonds with an endogenous default boundary.

[1] An option that becomes worthless once it falls short of the barrier at any point in time.

Another shortcoming of the original Merton model is the absence of taxes and bankruptcy costs. Leland (1994) addresses this by incorporating these elements, creating a trade-off model. Leland and Toft (1996) extends this concept by introducing an endogenous default boundary. The default decision is made to maximize equity value. If default is not optimal, firms should issue equity to service debt payments, further delaying default as much as possible.

Crosbie and Bohn (2003) explains the KMV model applied by Moody's. This model utilizes the Vasicek-Kealhofer model. The model treats equity as a perpetual down-and-out option on the underlying assets of a firm. Additionally, it allows for various types of liabilities, such as short-term, long-term, convertible debt, preferred equity, and common equity. A critical innovation to this model is the incorporation of a comprehensive default database establishing empirical default distributions. This distribution relates to the distance-to-default. This measures how close a firm is to defaulting on its obligations compared to the actual probability of default. Applying this, they create an expected default frequency, measuring the probability of default for various horizons.

Eom et al. (2004) conducts a comprehensive study of five different structural models, evaluating their ability to predict credit spreads. This study includes models with different extensions to the Merton model. These extensions include coupons, the possibility of default before maturity, variability in recovery rates, and stochastic interest rates. The models tested are Geske (1979), Longstaff and Schwartz (1995), Leland and Toft (1996), Collin-Dufresne and Goldstein (2001), and an extended Merton model. All models encounter difficulty accurately predicting credit spreads. Notably, the extended Merton model and Geske model predict too low credit spreads on average. In contrast, the remaining models predict too high credit spreads on average.

3.4 Reduced Form Models

Reduced form models, first introduced by Jarrow and Turnbull (1995), models default as an exogenous, pure statistical event. These models are characterized by their flexibility in functional form, enabling them to closely fit a narrow collection of spreads. This results in good in-sample results but limited out-of-sample predictive power.

Jarrow (2011) presents a comparative analysis of reduced form and structural models, highlighting the fundamental difference in the assumption of information. He argues that reduced form models assume asymmetric information, implying that lenders possess less information than the firm's management. In contrast, structural models assume symmetric information. Jarrow (2011) argues that due to the structural model's misalignment with the real-world scenario of asymmetric information, it is inappropriate for pricing credit risk. He further advocates for reduced form models as they align with the realities of asymmetric information in the financial markets.

In recent times, the interest in studies on reduced form models has increased. This is motivated by the reliance on bond prices as a primary input. Comprehensive bond pricing data has historically been challenging to access, especially in less transparent markets such as the Norwegian bond market. The increasing availability of such data is likely to enhance the attractiveness of reduced form models in credit risk analysis.

3.5 Other Sources of Risk Premium

The previous sections have provided a foundational overview of different models and theories used to calculate the credit risk of corporate bonds. Empirical findings suggest that there are other factors beyond credit risk to the credit spread component (Sæbø, 2015). This unexplained portion of the credit spread component is known as the *credit spread puzzle*.

Sæbø (2015) argues if investors only are compensated for the expected loss due to default, it implies they are risk neutral. However, this is unlikely as most investors have some degree of risk aversion. Consequently, investors demand additional compensation beyond the expected loss. Sæbø states that the credit spread puzzle is highly present in the Norwegian bond market. Indicating non-default related risks such as liquidity, and Fama French factors partly contributes to the explanation of the credit spread puzzle.

Previous studies on the US bond market include taxation as an explanatory factor of the credit spread puzzle. Elton et al. (2001), for instance, finds taxation to explain a significant portion of the credit spread puzzle for US bonds. However, since Norwegian corporate and government bonds are taxed identically, taxation is non-relevant for the Norwegian credit spread puzzle.

4 Data

This chapter delves into the data collection process, covering bonds, financial data, and market metrics. We will present our assumptions and shed light on the decision-making process for determining our final sample.

4.1 Data Sources

4.1.1 Bond Prices

Nordic Bond Pricing (NBP) provided us with daily theoretical bond prices spanning from 2014 to 2023. The primary focus of this thesis is corporate bonds. Hence, the provided sample excludes bonds issued by the public sector as well as banking (further explained in section 4.3). NBP is an independent third-party provider that evaluates bond pricing. They cover bonds issued in the Nordics, with an emphasis on the Norwegian bond market. NBP's valuation methodology uses several information sources, such as dealer/broker indications, market conditions, news, and proprietary algorithms (Nordic Bond Pricing, 2023). Furthermore, NBP provided us with their yield calculation.

Given the over-the-counter nature of the Norwegian bond market, obtaining transaction prices remains a challenging task. However, consultation with experts from SEB and Sparebanken 1 Markets, led us to conclude that NBP's pricing method serves as an adequate substitute for transaction prices.

4.1.2 Bond Characteristics

To obtain bond characteristics for bonds issued in our sample, Stamdata granted us temporary access to their database. Stamdata is a leading source of fixed income market information with an extensive database on Nordic bonds. This database offers insights into the bonds, such as industry classification, coupon types, and the risk grade at the time of issuance. Other bond characteristics included are *reference rate, coupon margin, issue date, maturity date, currency, bond market* and *issued amount.*

4.2 Preliminary Bond Sample Overview

The initial integration of price data from NBP and bond characteristics from Stamdata by ISIN results in an initial sample comprising 4 439 distinct bonds. Table 4.1 showcases the risk grade distribution of the preliminary sample. IG is the most prevalent risk grade, accounting for 72%. The total issued amount is 1 681 622 million Norwegian Kroner (NOK). IG bonds represent 75% of the total issued amount, and HY bonds constitute the remaining 25%.

Table 4.1: Risk grade - Preliminary bond sample

Risk grade	n	Percentage	Total issued amount (mNOK)	Percentage
IG	3 205	72	1 253 710	75
HY	1 234	28	427 912	25
Total	4 439	100	1 681 622	100

A descriptive table of the preliminary bond sample, categorized by risk grade. It includes the number of distinct bonds (n) with the corresponding percentage distribution. Additionally, it includes the total issued amount with the corresponding percentage distribution.

The preliminary bond sample contains 2 630 795 daily price observations. IG comprises 59% of the observations, and HY bonds 41%. This distribution indicates there are more observations per distinct HY bond compared to IG bonds.

Table 4.2: Number of observations by risk grade

Risk grade	n	Percentage
IG	1 540 540	59
HY	1 090 255	41
Total	2 630 795	100

This table presents the number of observations in the preliminary bond sample, categorized by risk grade.

Table 4.3 showcases the industry distribution for the preliminary bond sample. Transportation is the dominant sector, followed by real estate, banking, and utilities. These sectors represent approximately 74% of the issued bonds and account for 68% of the total issued amount.

Table 4.3: Industry - Preliminary bond sample

Industry	n	Percentage	Total issued amount (mNOK)	Percentage
Transportation	1 165	26	340 015	20
Real Estate	886	20	381 281	23
Bank	640	14	95 474	6
Utilities	599	14	317 421	19
Oil and Gas Services	189	4	69 867	4
Convenience Goods	188	4	97 280	6
Industry	181	4	108 555	6
Shipping	138	3	87 408	5
Consumer Services	102	2	34 861	2
Finance	71	2	14 678	1
Oil and Gas E&P	67	2	22 343	1
Telecom/IT	67	2	35 464	2
Insurance	39	1	24 425	2
Seafood	29	1	20 572	1
Pulp, Paper and Forestry	27	1	6 146	0
Media	20	0	9 500	1
Health Care	19	0	10 578	1
Auto	8	0	2 827	0
Agriculture	2	0	225	0
Government	1	0	700	0
Public Sector	1	0	2 000	0
Total	4 439	100	1 681 622	100

A descriptive table of the preliminary bond sample, categorized by industry. It includes the number of distinct bonds (n) with the corresponding percentage distribution. Additionally, it includes the total issued amount with the corresponding percentage distribution.

The preliminary sample is dominated by fixed- and floating rate bonds. Other coupon types are zero coupon bond, step rate, and adjustable rate.

Table 4.4: Coupon type - Preliminary bond sample

Coupon type	n	Percentage	Total issued amount (mNOK)	Percentage
Fixed Rate	2 631	59	906 407	54
Floating Rate	1 705	38	738 873	44
Zero Coupon Bond	56	1	15 871	1
Step Rate	38	1	17 605	1
Adjustable Rate	9	0	2 866	0
Total	4 439	100	1 681 622	100

A descriptive table of the preliminary bond sample, categorized by coupon type. It includes the number of distinct bonds (n) with the corresponding percentage distribution. Additionally, it includes the total issued amount with the corresponding percentage distribution.

4.3 Data Processing

Credit spread analysis requires a relatively homogeneous sample to avoid biased results. A bond with callable features will have a higher spread compared to a vanilla bond due to the embedded downside for the bondholder. Following this, we will present our data filtering process.

As the extended Merton model (see chapter 5) requires market data such as market capitalization, we have excluded non-listed companies from our analysis. Furthermore, we follow the method of Eom et al. (2004) to omit banking and finance. As finance and banking usually have higher leverage ratios compared to other industries, this enables us to compare leverage ratios across industries. Additionally, we focus solely on senior unsecured bonds with bullet as the redemption type. Any bonds not denominated in NOK, not listed on either the Nordic ABM or Oslo Stock Exchange (OSE), or those with features deviating from vanilla bonds were also excluded.

We omit bonds with a maturity of less than one year, as they are highly unlikely to be actively traded. A manual assessment of our sample shows that none of the firms defaulted during our sample period. This eliminates the need to address potential default issues. Furthermore, our analysis includes pricing data spanning from 2014 to 2022. We exclude observations from 2023 as financial statements for 2023 are not available.

Additionally, we restrict our price data to the last recorded price of each month. This better aligns our price data with annual financial data. Monthly data mitigates autocorrelation issues. A better alternative is yearly pricing data, but it results in an insufficient number of observations to calculate the roll-spread (see section 5.4.6). Hence, monthly data is most viable.

A manual review of the sample reveals that ISIN[2] NO0010715931, issued by Entra ASA, was issued before the company was publicly listed. For this reason, we omit this bond.

[2]International Securities Identification Number

4.4 Final Bond Sample Overview

The final sample consists of 37 distinct bonds issued between 2014 – 2022. The total issued amount is 33 925 million NOK. Compared to the initial sample, there are 0.8% distinct bonds left and 2% of the issued amount. The sample is evenly distributed between IG and HY, whereas 51% are IG and 49% are HY. Furthermore, we see that IG accounts for 58% of the total issued amount. The data processing results in an even sample distribution by risk grade and total issued amount.

Most of the companies in the final sample are not officially rated. Therefore, we choose to rely on Stamdata's risk grade classification. This classification is given upon the issue date and remains static throughout the time series. This can potentially disturb our results. However, it is unlikely to cause systematic errors.

Table 4.5: Risk grade - Final bond sample

Risk grade	n	Percentage	Total issued amount (mNOK)	Percentage
IG	19	51	19 625	58
HY	18	49	14 300	42
Total	37	100	33 925	100

A descriptive table of the final bond sample, categorized by risk grade. It includes the number of distinct bonds (n) with the corresponding percentage distribution. Additionally, it includes the total issued amount with the corresponding percentage distribution.

The number of observations in the final sample is reduced to 1 669 from the initial 2 630 795. This accounts for the removal of 99.94% observations. Notably, the distribution of observations by risk grade is more balanced. IG constitutes 53% of the sample observations, while HY makes up the remaining 47%.

Table 4.6: Number of observations by risk grade

Risk grade	n	Percentage
IG	881	53
HY	788	47
Total	1 669	100

This table presents the number of observations in the final bond sample, categorized by risk grade.

Shipping, industry, and real estate have emerged as the most prevalent sectors, accounting for 62% of the sample's issuances. This distribution mirrors the capital-intensive and oil-dependent nature of the Norwegian economy. Notably, we observe that the sector distribution between the risk grades differs (see table A.1 and A.2). We find that the HY sample contains mostly capital-intensive and oil-dependent sectors, such as shipping. Conversely, the IG sample has a broader exposure to less capital-intensive and oil-dependent sectors.

Table 4.7: Industry - Final bond sample

Industry	n	Percentage	Total issued amount (mNOK)	Percentage
Shipping	9	24	7 550	22
Industry	8	22	10 150	30
Real Estate	6	16	5 750	17
Media	4	11	2 500	7
Transportation	3	8	3 500	10
Convenience Goods	2	5	2 175	6
Pulp Paper and Forestry	2	5	800	2
Oil and Gas Services	1	3	700	2
Seafood	1	3	500	2
Telecom IT	1	3	300	1
Total	37	100	33 925	100

A descriptive table of the final bond sample, categorized by industry. It includes the number of distinct bonds (n) with the corresponding percentage distribution. Additionally, it includes the total issued amount with the corresponding percentage distribution.

Further, table 4.8 reveals that the vast majority of the sample consists of floating rate bonds. Floating rate bonds constitute 89% of the sample. The reference rate is a three-month NIBOR (3M NIBOR) rate.

Table 4.8: Coupon type - Final bond sample

Coupon type	n	Percentage	Total issued amount (mNOK)	Percentage
Floating Rate Note	33	89	30 625	90
Fixed Rate	4	11	3 300	10
Total	37	100	33 925	100

A descriptive table of the final bond sample, categorized by coupon type. It includes the number of distinct bonds (n) with the corresponding percentage distribution. Additionally, it includes the total issued amount with the corresponding percentage distribution.

4.5 Financial- and Market Data

This section presents the sampling process for financial- and market data used to complete the final data set.

4.5.1 Financial Data

We utilize Refinitv's database to collect annual financial statements. This is matched with the corresponding year's pricing data. This is in spite of potential timing discrepancies between the public release of financial statements and the information available to bond investors at any given time. Furthermore, the varying timing of releasing financial statements across firms poses another challenge for precise matching. Therefore, this implementation represents the most feasible way to consolidate the data. We acknowledge that this approach could potentially disturb the results. However, it is unlikely to cause systematic errors.

4.5.2 Market Data

Market data covering stock prices, total shares outstanding, and time series data for 3M NIBOR is gathered from Refinitiv. Additionally, time series data for Norwegian government bonds spanning available maturities from 3 months to 10 years is sourced from Bloomberg.

4.5.3 Currency conversion

Bonds issued by foreign entities require currency conversion. Refinitiv's database automates daily market price conversions, while yearly accounting data utilizes an average annual foreign exchange rate.

4.6 Default and Recovery Data

The extended Merton model requires input on recovery rates. Ytterdal and Knappskog (2015) leveraged Stamdata's recovery and default data to create estimates for a suitable recovery rate. However, access restrictions limit our ability to model recovery rates.

Consequently, we adopt a similar recovery rate to Eom et al. (2004) at 51.31% across all observations. Recovery rate is further discussed in section 5.3.4.

5 Methodology

This section outlines the methodology applied to calculate credit spreads, adopting the extended Merton model as introduced by Eom et al. (2004). Section 5.1 presents our estimations of credit spread and mispricing. Section 5.2 introduces the model in detail, while section 5.3 describes the parameters incorporated in our model. Section 5.4 and 5.5 outline the approach for the regression analysis and our variable selection.

5.1 Estimating Credit Spread and Mispricing

To assess mispricing and examine the strength of various explanatory variables, we need the observed and modelled credit spreads. Utilizing the Extended Merton model, we calculate the model yields. The observed yields are gathered from the data set provided by NBP. This enables us to compute the observed credit spreads in the market and those predicted by the model. This thesis defines credit spread as the difference in yield between a corporate bond and a risk-free rate with similar time to maturity.

$$\text{Credit spread}_{i,t} = YTM_{\text{Corporate}_{i,t}} - YTM_{\text{Risk-free}_{i,t}} \tag{5.1}$$

Following the approach of Sæbø (2015), mispricing is calculated as the difference between the observed and the predicted model credit spreads.

$$\text{Misprice}_{i,t} = \text{Observed credit spread}_{i,t} - \text{Model credit spread}_{i,t} \tag{5.2}$$

5.2 Extended Merton Model

The Extended Merton model (Eom et al., 2004) augments the original model presented by Merton (1974). It accommodates the dynamic of pricing a coupon bond and the potential for default prior to maturity. Additionally, the model incorporates a payout ratio, allowing for asset drift. This can, in turn, increase the probability of default. The model treats a coupon paying bond as a portfolio of zero-coupon bonds. It considers a bond with maturity T, a unit face value, and semi-annual coupon payments. The annual coupon payment is denoted by c. Furthermore, the model assumes that $2T$ is an integer, which ensures that a bond's maturity at a given time is in half-year increments to align with the assumption of semi-annual coupons. Similar to the Merton (1974) model, a firm's asset value follows a geometric Brownian motion.

The bond price $P(0,T)$ for a given maturity is calculated using equation 5.3. $D(0,T_i)$ denotes the present value at time zero for a risk-free zero-coupon bond with maturity T, represented by e^{-rT_i}. E^Q represents the expected value under risk neutral probabilities. I is a binary indicator function expressing if the value of the firm's assets exceeds or falls below the default barrier K. Further, W represents the *recovery rate*. Equation 5.3 can be split into two parts. The top part shows the expected value of future coupon payments on a coupon date, discounted by $D(0,T_i)$. Should the firm's asset value surpass the default barrier, the expected payout can be expressed as $\mathbb{E}^Q\left[I_{\{V_{T_i}\geq K\}}\right]\frac{c}{2}$. Conversely, if the firm's assets fall below the default barrier, the expected payout can be expressed as $\mathbb{E}^Q\left[I_{\{V_{T_i}<K\}}\min\left(\frac{wc}{2},V_{T_i}\right)\right]$. The lower part of equation 5.3 mirrors the functions of the top part but includes the principal payment in addition to the coupon at maturity.

$$\begin{aligned} P(0,T) = \sum_{i=1}^{2T-1} & D(0,T_i)\mathbb{E}^Q\left[\left(\frac{c}{2}\right)I_{\{V_{T_i}\geq K\}} + \min\left(\frac{wc}{2},V_{T_i}\right)I_{\{V_{T_i}<K\}}\right] \\ & + D(0,T)\mathbb{E}^Q\left[\left(1+\frac{c}{2}\right)I_{\{V_T\geq K\}} + \min\left(w\left(1+\frac{c}{2}\right),V_T\right)I_{\{V_T<K\}}\right] \end{aligned} \tag{5.3}$$

Eom et al. (2004) further introduces equation 5.4, and 5.5 to complete the model.

$$\mathbb{E}^Q\left[I_{\{V_t\geq K\}}\right] = N(d_2(K,t)) \tag{5.4}$$

$$\mathbb{E}^Q\left[I_{\{V_t<K\}}\min(\Psi,V_t)\right] = V_0D(0,t)^{-1}e^{-\delta t}N(-d_1(\Psi,t)) + \Psi\left[N(d_2(\Psi,t)) - N(d_2(K,t))\right] \tag{5.5}$$

On a coupon date, the *recovery value* is $\Psi = \frac{wc}{2}$, while on the last payment day, $\Psi = \left(w\left(1+\frac{c}{2}\right)\right)$. If V_t is greater than the default barrier K, the promised cash flow is fully paid. However, if V_t falls short of the default barrier but is greater than Ψ, the payment is limited to Ψ. If V_t falls short of both Ψ and K the payment equals V_t. $N(.)$ is the cumulative normal function where

$$d_1(x,t) = \frac{\ln\left(\frac{V_0}{xD(0,t)}\right) + \left(-\delta + \frac{\sigma_V^2}{2}\right)t}{\sigma_V\sqrt{t}} \tag{5.6}$$

$$d_2(x,t) = d_1(x,t) - \sigma_V\sqrt{t} \tag{5.7}$$

By combining the equations above, we calculate the price of a bond with maturity T. This is further used to calculate the model credit spread used in our analysis.

5.3 Model Parameters

The Extended Merton model incorporates several parameters gathered from different sources. Table 5.1 presents the parameters, estimation method, and data source.

Table 5.1: Model parameters

Parameter	**Notation**	**Description**	**Data Source**
		Bond Features	
Coupon	c	Given	Stamdata
Default Barrier	K	Short-term debt + 0.5 * Long-term debt	Refinitiv
Maturity	T	Given	Stamdata
Recovery Rate	w	See Section 5.3.4	
		Firm Characteristics	
Asset Value	V	Book value of debt + Market value of equity	Refinitiv
Asset Volatility	σ_V	See Section 5.3.1	Refinitiv
Payout Ratio	δ	See Section 5.3.2	Refinitiv
		Interest Rate	
Risk-free Rate	r	Section 5.3.5	Bloomberg

Summary of the model parameters used in the extended Merton model. It includes their notation, description, and data sources.

5.3.1 Asset Value and Asset Volatility

Asset value and asset volatility are non-observable values, consequently, a weakness of structural models. Section 3.2.1 describes how a firm's equity value can be priced as a European call option using the Black-Scholes option pricing framework. This framework shows the relationship between a firm's asset value (V), asset volatility (σ_V), time to maturity (T), interest rate (r) and face value of debt (B). Equation 5.8 shows how one can calculate the equity value using the Black-Scholes framework,

$$\text{Equity} = VN(d_1) - Be^{-rT}N(d_2) \tag{5.8}$$

where

$$d_1(x,t) = \frac{\ln\left(\frac{V_0}{xD(0,t)}\right) + \left(-\delta + \frac{\sigma_V^2}{2}\right)t}{\sigma_V\sqrt{t}} \tag{5.9}$$

and

$$d_2(x,t) = d_1(x,t) - \sigma_V\sqrt{t} \tag{5.10}$$

Furthermore, by applying the Black-Scholes framework, we get the relationship presented in equation 5.11. This allows us to calculate the two endogenous variables asset volatility and asset value by solving equation 5.8 and 5.11 simultaneously.

$$\sigma_E = N(d_1) \times \frac{V}{E} \times \sigma_V \tag{5.11}$$

Required inputs for solving these equations are equity value (E), equity volatility (σ_E), and an estimate for the face value of debt (B). E is calculated as the market capitalization of equity at each point in time.

There are different approaches to the calculation of equity volatility. For instance, sophisticated methods like Autoregressive Conditional Heteroskedasticity (ARCH), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) modelling, or simpler approaches such as moving average and exponential weighted moving average. Ytterdal and Knappskog (2015) uses five years of monthly data to calculate σ_E, while Eom et al. (2004) uses different estimation windows as well as bond implied volatility. Eom et al. (2004) finds that the use of bond implied volatility results in smaller pricing errors compared to equity returns. However, due to ease of implementation, we follow a similar method as Eskerud (2017) by calculating equity volatility as a 150-day moving average. Similar to both Eom et al. (2004) and Eskerud (2017), we define asset value as the book value of debt plus the market capitalization of equity.

Through these estimations, equation 5.11 is utilized to calculate asset volatility, solving it iteratively using R.

The absence of debt volatility can be explained by the relationship in equation 5.11. Volatility of risk-free debt is zero, leaving asset volatility to be a function of equity volatility. However, most businesses deviate from this assumption as they often have several sources of debt, which usually isn't risk-free. In reality, debt volatility should be accounted for. But as the formula doesn't account for this, it is not relevant in this instance.

5.3.2 Payout Ratio

Payout ratio is another enhancing feature of the extended Merton model. This variable controls the outflow of cash in the form of dividends, share repurchases, and interest paid to equity holders. It captures the asset drift, which in turn could increase the firm's probability of default. We define the payout ratio as follows:

$$\frac{\text{Dividends paid} + \text{share repurchases} + \text{interest to equity holders}}{\text{Total assets}} \tag{5.12}$$

Similar to Eskerud (2017), total assets are defined as the total book value of assets, and the time of observation is the prior year. This is because dividends usually get paid out the following year. We follow the Eskerud (2017) implementation, as we assume that for each point in time, the payout ratio is constant. This is regardless of the firm's future performance.

5.3.3 Default Barrier

The default barrier is the firm's default condition. If the firm's asset value at time T falls short of the default barrier, the model considers it to be insolvent. Previous literature proposes different ways to define the default barrier. A commonly used measure is the total book value of debt. This way of defining the default barrier has been implemented by Eom et al. (2004) and Feldhütter and Schaefer (2018). However, firms are often able to renegotiate debt with longer maturities, making it unlikely that all debt will mature during the estimation period. Thus, it is reasonable for the default barrier to be less than the total book value of debt. Other papers utilize short-term debt plus a fraction of the long-term debt given by Y. Afik et al. (2012) conducts a sensitivity analysis on the Merton model, testing for different values of Y other than the market standard of 0.5. They find that the use of different Y yields no significant impact on the model's accuracy. Therefore, we implement a default barrier given by

$$\text{Default barrier} = \text{Short-term debt} + Y * \text{Long-term debt} \tag{5.13}$$

where Y equals the market standard of 0.5.

5.3.4 Recovery Rate

The original Merton model assumes creditors receive 100% of the remaining firm value in the event of default. In reality, the true recovery rate varies and is often lower than 100%. A firm is often subject to different bankruptcy costs, such as filing, legal, and accounting fees, causing the recovery rate to be lower than 100%. Longstaff and Schwartz (1995) argues that the recovery rate is the outcome of a bargaining process rather than a systematic process. They argue that modeling recovery rates is unnecessary as it is an unsystematic and unpredictable variable. However, there are studies that have modelled recovery rates. Keenan et al. (1999), for instance, finds that the average recovery rate for their sample is 51.31%. This is the recovery rate Eom et al. (2004) utilizes in his study. Other studies, such as Ytterdal and Knappskog (2015) try modelling recovery rates, but due to inconclusive results, they implement a static recovery rate of 40%. Due to data restrictions limiting our ability to model recovery rate, we adopt a uniform recovery rate of 51.31% for all observations, similar to Eom et al. (2004)

Eskerud (2017) conducts a sensitivity analysis of model mispricing to change in recovery rates. He finds mispricing to be sensitive to variations in recovery rates. This likely stems from differences in actual recovery rates across industries and risk grades. We acknowledge that not accounting for varying recovery rates across different industries and risk grades could be considered a limitation. Therefore, the interpretation of results should be approached with caution.

5.3.5 Term Structure of Risk-free Interest Rates

Another enhancement to the original Merton (1974) model is the incorporation of stochastic interest rates. This better reflects real-world interest rate dynamics and uncertainties in the market. Eom et al. (2004) allows for the option to utilize either the Nelson-Siegel or the Vasicek model. Due to familiarity, we incorporate the Nelson-Siegel model.

The model's objective is to minimize the sum of the squared error deviation between observed market yields and the model yield. The yield of a bond, $y_t(m)$, with maturity m, is modelled together with a decay factor, λ. This gives us the following equation formulated by Nelson and Siegel (1987).

$$y_t(m) = \beta_{t0} + \beta_1 \frac{1 - e^{-m/\lambda}}{m/\lambda} + \beta_2 \left(\frac{1 - e^{-m/\lambda}}{m/\lambda} - e^{-m/\lambda} \right) \tag{5.14}$$

Solving equation 5.14 through the method of linear least squares in R, we find the best fitting values for the coefficients. This allows us to interpolate and extrapolate missing maturities. The result is a fitted yield curve at each moment in time.

We utilize Norwegian government bonds as the risk-free rate. It is generally acknowledged that no asset is entirely risk-free. However, Norwegian government bonds are considered the safest asset class. Hence, we find Norwegian government bonds suitable as a proxy for a risk-free rate.

An alternative approach is the use of swap rates plus/minus a spread. Sæbø (2015) further discusses this topic. He claims that the traditional approach has been to utilize government bonds. However, this yield can be affected by other factors such as a scarcity premium due to monetary easing. Hence, he applies swap rates less 10 bps as proxy.

We conduct a sample test using swap rates similar to Sæbø (2015). We find the results to yield similar results to the government risk-free rates. For that reason, and the Norwegian government's low risk profile, we deem government bonds to be an appropriate choice as risk-free rates.

5.4 Regression Analysis: Defining the Variables

This thesis has two main objectives. First, to uncover and analyze how non-default related variables affect mispricing between HY and IG. Exploring both their relative magnitude and explanatory power. Second, to predict the determinants of the difference in credit spread between HY and IG. This section introduces the variables used in the first part of the analysis. Section 5.5 introduces additional variables incorporated in the second part of the analysis.

Part one of the analysis presents two regression outputs. One output with respect to HY and one for IG. These outputs include non-default related variables to explore mispricing differences between the risk grades. Both in terms of explanatory power and their relative magnitude. The chosen variables are based on academic research and economic intuition. Similar to Sæbø (2011) we investigate how non-default related factors, such as liquidity- and market risk can explain mispricing. Table 5.2 presents the included variables in the first two regressions. The remaining sub-section explains the rationale behind the incorporation of these variables.

Table 5.2: Regression model - Variables

Variable Class	Variable	Description
Dependent Variable	Mispricing	Observed spread - Model spread
Explanatory Variables	Industry	Dummy variable
	Market-to-book	Market capitalization/Book value of equity
	Covid-19	Dummy variable
	OSEBX	Log return for OSEBX
	Oil price	Log return for Oil price
	Roll-spread	See F.1
	TED-spread	3M NIBOR - 3M Government yield

This table outlines the dependent and independent regression variables included in part one of the analysis.

5.4.1 Industry

Similar to Sæbø (2011), we include a dummy variable for industries. He finds industry as an important variable in explaining the variation in mispricing. A probable reason for industry explaining a great part of the variation can be the industries sensitivity to different risks. This can be cyclical tendencies or other industry characteristics that make investors require an additional premium to bear such risks. By including this dummy, we hope to capture industry specific risks.

5.4.2 Market-to-book

Market-to-book is market capitalization divided by the book value of equity. It indicates if the share price is under- or overpriced. High market-to-book implies growth stocks, whereas low market-to-book indicates value stocks. Growth stocks are often associated with higher risk, making it interesting to investigate if this relationship can be applied to credit risk. Sæbø (2011) finds the variable unstable in his analysis, thus difficult to draw inferences. However, based on economic intuition as well as it is deemed an important factor in the equity market, we find it interesting to include.

5.4.3 Covid-19

Our sample contains data before and after the covid-19 crisis. Therefore, it is of interest to investigate if the presence of the crisis affected spreads in the bond market. Similar to Sæbø (2011), which includes a dummy indicating the start of the financial crisis we include a similar dummy for the start of covid-19. We define 12. March 2020 as the starting point of the crisis, as this was the date the Norwegian lockdown began. Unlike the financial crisis, covid-19 was rooted in a pandemic rather than a pure financial crisis. For this reason, we expect the crisis will impact mispricing, but unsure to what extent.

5.4.4 Oslo Stock Exchange Benchmark Index

The inclusion of excess returns on the Oslo Stock Exchange Benchmark Index (OSEBX) is based on economic intuition. As equity markets rise, one could expect the overall perception of firms to be less risky. Sæbø (2011) finds this variable insignificant and unable to explain additional variation in mispricing. Nevertheless, it is economically intuitive and interesting to include it.

5.4.5 Oil Price

Our sample is predominantly oil-dependent, mirroring the broader Norwegian economy. Table 4.7 presents that oil-dependent industries such as shipping, oil and gas services, and industry constitute 49% of the final sample. It is plausible that there can be a relationship between the oil price and the dependent variable. Sæbø (2011) found the oil price variable to yield inconclusive results. Regardless, we find it interesting to include.

5.4.6 Roll-spread

The Roll-spread (Roll, 1984) is a commonly used liquidity measure used to calculate transaction costs for less traded bonds. The Roll-spread assumes that price changes only occur in response to additional market information. This eliminates serial dependencies on successive price changes. By estimating the serial covariance of price returns, we can calculate a proxy for transaction costs (see appendix F.1 for formula description). Schestag et al. (2016) finds this measure to strongly correlate with other liquidity measures, indicating its ability to proxy as a liquidity measure. An additional benefit is that it requires low data and processing demands. The absence of transaction data prohibits us from calculating actual transaction costs. Consequently, we find this liquidity measure to be a suitable alternative. Following the approach of Corwin and Schultz (2012), negative and zero values are omitted.

Liquidity has been uncovered as a significant explanatory variable for credit spreads in the bond market. Riis-Johansen and Kronberg (2021), for instance, investigated several liquidity measures for the Norwegian HY bond market. Their findings suggest that around 20.5% to 26.9% of the variation in credit spread can be attributed to a liquidity risk premium.

5.4.7 TED-spread

TED-spread is short for Treasury EuroDollar spread. It is defined as the difference between the 3-month LIBOR and the yield of 3-month US government bonds. It is used to measure market risk on the US market. We apply this formula to the Norwegian market. The Norwegian TED-spread is calculated as the difference between the 3-month NIBOR and the yield of a 3-month Norwegian government bond. An increase in the 3-month NIBOR compared to the corresponding government yield results in heightened counterparty risk (Taylor & Williams, 2009). Fluctuating counterparty risk correspondingly impacts market risk. Essentially, an increase in counterparty risk tends to result in increased risk in the market. Therefore, incorporating TED-spread can provide insights into market risk.

5.5 Isolated Difference Regression Analysis: Defining the Variables

Part two of the analysis is a regression output with the mean credit spread difference between HY and IG as the dependent variable. Since bonds with different bond features are compared, firm-specific explanatory variables are included. This captures irregularities in bond features. Firm-specific variables are computed as the difference in mean values between HY and IG. Hence, the number of observations is reduced to 92 from the original 1 669. This allows us to isolate and predict the determinants of the difference in credit spread.

Table 5.3: Isolated difference regression model - Variables

Variable Class	**Variable**	**Description**
Dependent	Mean credit spread difference	HY mean observed spread - IG mean observed spread
Independent	Coupon	HY mean coupon - IG mean coupon
	Maturity	HY mean maturity - IG mean maturity
	Leverage	HY mean leverage - IG mean leverage
	Asset volatility	HY mean asset volatility - IG mean asset volatility
	OSEBX	Log return for OSEBX
	Oil price	Log return for Oil price
	TED-spread	Market risk
	Credit risk	Difference in mean proportion credit spread explained by Merton

Overview of the dependent and independent regression variables included in part two of the analysis. It includes variable classes and their descriptions.

5.5.1 Leverage

Leverage is included as we observe a noticeable difference in leverage between HY and IG issuers.[3] Therefore, it is of interest to investigate whether the credit spread difference between HY and IG is due to a disparity in leverage. Leverage is calculated using equation 5.15.

$$\text{Leverage} = \frac{\text{Book value of debt}}{\text{Market Cap}} \tag{5.15}$$

5.5.2 Asset Volatility

One important factor determining default risk is asset volatility. This is because higher asset volatility entails an increased probability of asset value falling below the default barrier. Consequently, it is of interest to investigate whether changes in asset volatility affect the difference in credit spread between HY and IG.

Eom et al. (2004) finds that the extended Merton model underpredicts credit spread for firms perceived to be safer, e.g., lower asset volatility. This is further incentive to uncover the possible relationship between asset volatility and credit spread differences.

5.5.3 Credit Risk

Credit risk is calculated as the model credit spread divided by the observed credit spread. It is included in the regression to capture the implied default risk in both risk grades. Particularly if differences in implied default risk will affect the overall credit spread difference between HY and IG bonds.

[3]See table 6.5

6 Analysis

This chapter is structured as follows: Section 6.1 tests the data set against fundamental assumptions for regression analysis. In section 6.2 we analyze and discuss the model performance. Particularly the model's ability to calculate spreads. Further analysis of the model performance is elaborated in section 6.3. Section 6.4 presents regression analysis for both HY and IG. Finally, section 6.5 presents a regression analysis on the credit spread difference between HY and IG bonds.

6.1 Measure of Tendency and Variability

The data set is tested for ordinary least squares (OLS) regression model assumptions. Ensuring these assumptions hold is necessary for the regression output to have economic substance. This section is dedicated to investigating regression models that incorporate all independent variables.[4] For analysis of regression models with only one independent variable, see appendix E.

6.1.1 Autocorrelation (Durbin-Watson)

A common problem for time series data is autocorrelation. This occurs when current observations correlate with past values (Smith, 2023). It is problematic because OLS regression assumes independence between observations. Daily observations are exposed to autocorrelation, as past news can have a lagged effect on current observations. We explain how we cope with this issue in section 4.3, where we convert the data set from daily to monthly observations. Furthermore, to ensure there is no autocorrelation on the y-variable, we performed a Durbin-Watson test on the residuals from the three regression outputs. The test returns values ranging from zero to four. Values near zero indicate positive autocorrelation and values close to four indicate negative autocorrelation. Values close to two suggest little autocorrelation. Table 6.1 shows that the IG sample has a relatively high autocorrelation with a value of 0.58. HY, on the other hand, is less exposed to autocorrelation, with a value of 1.81. Lastly, the regression incorporating the difference in credit spread between HY and IG has a value of 1.02, which indicates

[4] The models in scope are presented in table 6.8, 6.9 and 6.10

autocorrelation. To control for autocorrelation, all regression outputs are presented with Newey-West standard errors.[5]

Table 6.1: Durbin-Watson

Test result	P-value	Regression
0.59	0.01	IG
1.81	0.01	HY
1.02	0.01	(HY - IG)

The table presents the results of the Durbin-Watson test for all three regressions outputs.

6.1.2 Multicollinearity (VIF-test)

Regression models assume the correlation between independent variables is low. If this assumption is violated, multicollinearity is present. Consequently, one cannot make inferences about the X-variable's effect on the Y-variable. One way to test for multicollinearity is to calculate the variance inflation factor (VIF). This test tells how much an X-variable's variance is inflated due to the presence of multicollinearity (Shweta, 2021). In simpler terms, higher VIF values imply a higher correlation with other variables. We performed a VIF test for all independent variables present in all three regression models. A rule of thumb is that all values ranging between one and ten are acceptable. Appendix C shows that all variables passed the test, which suggests there is no multicollinearity present.

6.1.3 Heteroscedasticity

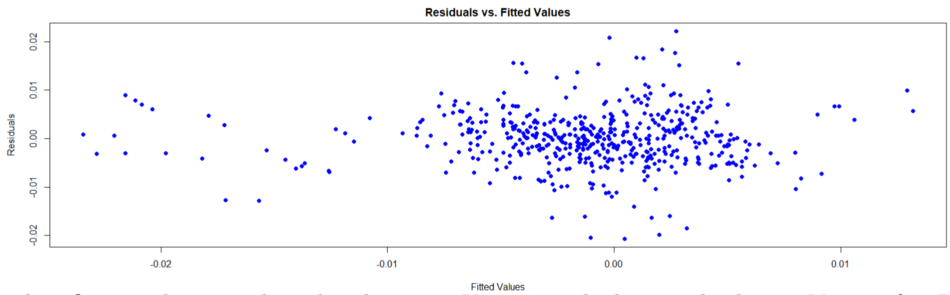
Heteroscedasticity is present when the variance in the error term is non-constant across all levels of independent variables (CFI, n.d.). This is problematic because OLS regressions assume residuals are drawn from a population of equal variance. By plotting the model's predicted values against the residual, we can observe whether the assumption of no heteroscedasticity is violated. Figure 6.1 shows that IG has no clear systematic trend on the residuals as fitted values increase, hinting at the presence of homoscedasticity. For HY, it appears that the residuals vary more as the fitted values increase. This indicates the presence of heteroscedasticity. For the difference regression, we observe a similar

[5] See appendix G for a brief explanation

trend as for HY. The variation in the residuals increases as the fitted values increase.

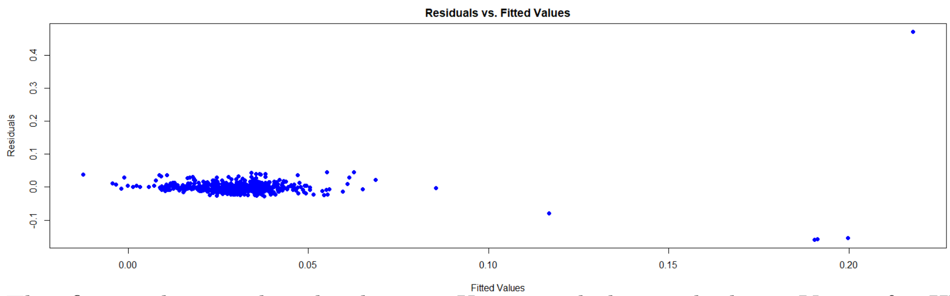
To further verify the presence of heteroscedasticity, we perform the Breusch-Pagan test. This test utilises hypothesis testing. The presence of homoscedasticity serves as the null hypothesis. If the p-value is less than 0.05, one can reject the null hypothesis and confirm the presence of heteroscedasticity. Appendix B shows that the null hypothesis is rejected for all models, confirming the presence of heteroscedasticity. For this reason, in addition to coping with autocorrelation, we implement the Newey-West standard errors to deal with the violation of homoscedasticity.

Figure 6.1: Residuals vs. Fitted Values for the IG Model



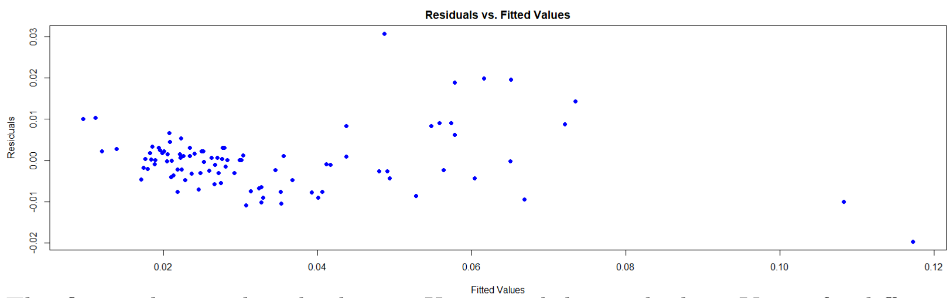
This figure plots predicted values on X-axis and the residuals on Y-axis for IG regression.

Figure 6.2: Residuals vs. Fitted Values for the HY Model



This figure plots predicted values on X-axis and the residuals on Y-axis for HY regression.

Figure 6.3: Residuals vs. Fitted Values for the (HY - IG) Model

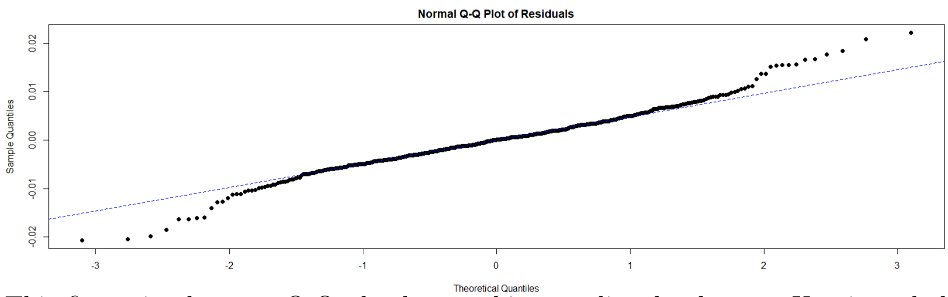


This figure plots predicted values on X-axis and the residuals on Y-axis for difference regression.

6.1.4 Normally Distributed Residuals

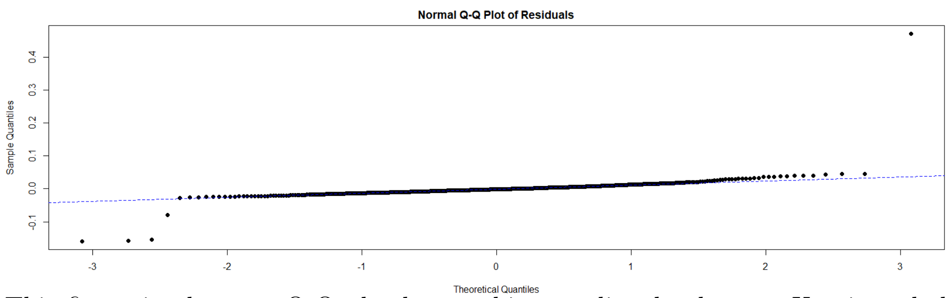
Another assumption of OLS regression models is that residuals are normally distributed. When this condition is violated, the model's statistical test suffers, but the beta estimators are still unbiased and efficient (Solutions, 2013). One way to investigate the probability distribution of residuals is through a quantile-quantile plot (Q-Q plot). This is a method to detect whether a data set follows a given distribution by plotting theoretical values on the x-axis and an observed sample on the y-axis (Grace-Martin, n.d.). The following figures present the plots for all three regression models. All three models yield plots that are tail-heavy, with the IG model being the most severe. This indicates all three models fail to produce valid p-values. However, violations of the normally distributed residuals are only problematic if the sample size is small. Typically, a sample size exceeding 30 observations is acceptable to meet the sample requirement (LaMorte, 2016). Consequently, our data set has an adequate size for the violation of normally distributed residuals to not be a major issue.

Figure 6.4: Normal Q-Q Plot of Residuals IG



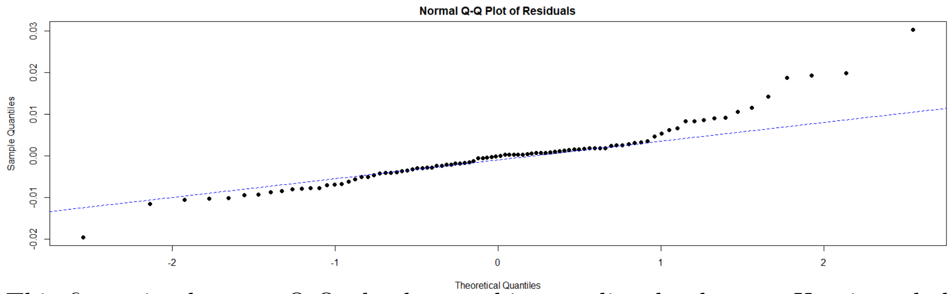
This figure implements Q-Q plot by graphing predicted values on X-axis and the observed values on Y-axis for IG regression.

Figure 6.5: Normal Q-Q Plot of Residuals HY



This figure implements Q-Q plot by graphing predicted values on X-axis and the observed values on Y-axis for HY regression.

Figure 6.6: Normal Q-Q Plot of Residuals (HY - IG) model



This figure implements Q-Q plot by graphing predicted values on X-axis and the observed values on Y-axis for difference regression.

6.2 Model Performance

6.2.1 Final Sample

Table 6.2 presents the performance of the Merton model with respect to the final sample containing both risk grades. On average, the model overprices bonds, thus underpredicting credit spreads compared to the observed values. This aligns with findings similar to Eom et al. (2004), Sæbø (2011) and Ytterdal and Knappskog (2015), that find the Extended Merton model to, on average, underpredict credit spreads. Table 6.2 shows that the model credit spread equals 36% of the observed credit spread. In other words, 36% of the observed credit spread is attributed to default risk. A closer inspection of the standard deviation, minimum, and maximum credit spread reveals that the model credit spread has considerably lower variation compared to observed credit spreads. The observed standard deviation is 4.32%, while the model standard deviation is 0.49%. This observation serves as an early indication of the model's inability to capture large portions of the variance in observed credit spreads.

Table 6.2: Descriptive Statistics Final Sample (%)

Metric	Observed Spread	Merton Spread
Mean	2.64	0.95
Median	1.66	0.99
Maximum	70.33	3.36
Minimum	-0.42	0.04
Std. Dev.	4.32	0.49

This table compares the observed spread with the spread estimated using the extended Merton model. This descriptive statistics is based on the final sample that includes both HY and IG.

6.2.2 High Yield

Eom et al. (2004) finds that the model tends to underpredict credit spreads for HY bonds, which aligns with the findings in table 6.3. The model, on average, predicts a credit spread of 0.89% compared to an observed credit spread of 4.55%. This means that default risk attributes to 20% of the HY bonds observed credit spread. Furthermore, the model has a lower standard deviation compared to the observed standard deviation. This indicates that the model struggles to capture the variance in credit spreads. The underprediction of credit spreads suggests that there are non-default related risk factors that the model doesn't capture.

Table 6.3: Descriptive Statistics for HY bonds (%)

Metric	Observed Spread	Merton Spread
Mean	4.55	0.89
Median	3.61	0.90
Maximum	70.33	2.28
Minimum	1.16	0.04
Std. Dev.	5.69	0.38

This table presents the descriptive statistics on credit spread for HY bonds. It compares the observed spread with the spread estimated using the extended Merton model.

6.2.3 Investment Grade

IG modelled credit spreads deviate from the findings for the final sample. Table 6.4 illustrates that the Merton model, on average, overpredicts credit spreads for IG bonds.

With a model average of 1.01% and an observed average of 0.94%, the model suggests that there is a default risk premium compared to the observed credit spread. This is peculiar as it implies that the observed credit spread can fully, in fact beyond, be attributed to default risk factors. Nevertheless, Eskerud (2017) finds the extended Merton model to overestimate credit spreads for his sample containing both risk grades. Another interesting comparison is Eom et al. (2004) findings for what the model considers safer bonds. Their findings suggest that the model, in general, does a poor job of pricing bonds with low leverage and asset volatility. Such bonds are associated with the smallest predicted credit spreads. Regarding asset volatility, our findings are in line with Eom et al. (2004), meaning bonds with higher asset volatility produce a higher model credit spread. To the contrary, leverage has a different effect on our findings compared to Eom et al. (2004). We find that bonds with lower leverage tend to have a higher model credit spread. These contradictory findings suggest either computational errors or sample-specific explanations, such as asset volatility. This is further discussed in section 6.2.4.

When comparing the standard deviation for the observed credit spread with the model credit spreads, it seems the model can capture a significant portion of the variance in observed credit spreads. However, as we will discuss in section 6.3, that is not entirely correct.

Table 6.4: Descriptive Statistics for IG bonds (%)

Metric	Observed Spread	Merton Spread
Mean	0.94	1.01
Median	0.93	1.07
Maximum	4.10	3.36
Minimum	-0.42	0.04
Std. Dev.	0.56	0.57

This table presents the descriptive statistics on credit spread for IG bonds. It compares the observed spread with the spread estimated using the extended Merton model.

6.2.4 Comparing High Yield and Investment Grade Spreads

An interesting observation from table 6.3 and 6.4 is that the model, on average, predicts lower credit spreads for HY compared to IG. This is unexpected, as IG issuers are often associated with lower credit risk due to their usual strong market positions, making them less exposed to default risk. A possible explanation could be the role of asset volatility in the model. Table 6.5 presents that HY issuers, on average, have higher equity volatility but lower asset volatility than IG issuers. This disparity in asset volatility can partly be explained by the leverage ratio. The relationship can be expressed through equation 5.11. Notably, HY issuers, on average, have a higher leverage ratio compared to IG issuers. As the equity volatility is unlevered, it reveals that IG issuers have the highest asset volatility. The result raises a potential justification for why IG bonds have higher model credit spreads than HY bonds given the significance of asset volatility in determining default risk, as Correia et al. (2017) emphasizes. Following this, we have conducted a sensitivity analysis to test the robustness of the model credit spread with respect to changes in asset volatility.[6]

Table 6.5: Financial Metrics (%)

Metric	HY	IG	Final Sample
Equity volatility	36.40	26.98	31.43
Asset volatility	10.24	17.95	14.31
Leverage	539.39	76.41	295.00

This table reports the average values of key financial metrics for HY, IG and the final sample of bonds.

6.3 Model Accuracy

We find the model for the final sample, on average, underpredict credit spreads which aligns with empirical findings such as Eom et al. (2004) and Sæbø (2011). However, segmenting the model performance by risk grade, we observe discrepancies between our findings and previous research for safer securities. To further assess the accuracy of the model, we analyze mispricing, defined by equation 5.2.

The credit spread component is likely to contain compensation for risks beyond default risk (Sæbø, 2015). As a result, one should expect mispricing to yield a positive value. Table 6.6 shows the results for IG bonds deviate from this notion as it yields negative mispricing. This is further verified by interpreting results from figure 6.7. This illustrates that the average mispricing for IG bonds is primarily centered around zero with a modest skew towards negative values. On the contrary, mispricing for HY bonds leans heavily

[6]See chapter 7

towards positive values, which seems both logical and aligns with findings from Eom et al. (2004) and Sæbø (2015).

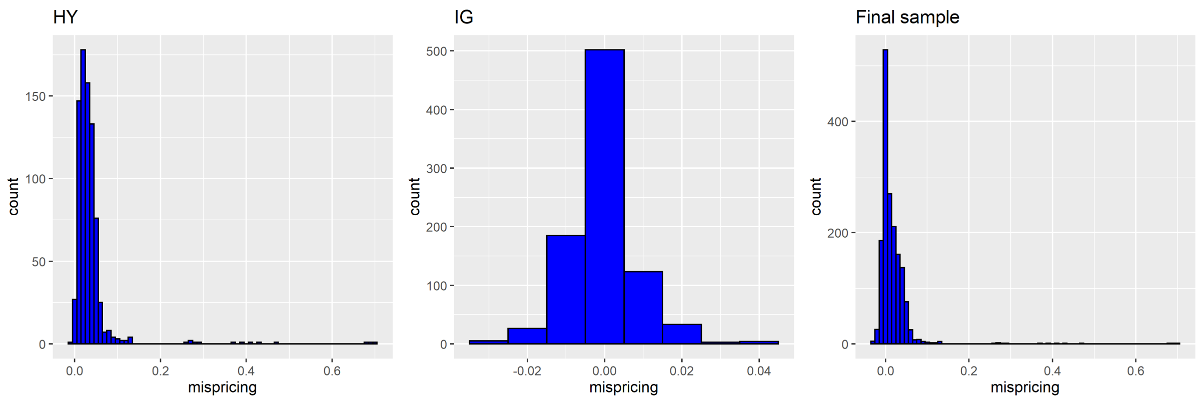
Furthermore, table 6.6 reveals the standard deviation for IG mispricing to be 0.86% and 5.77% for HY. A higher standard deviation indicates a higher degree of model uncertainty, suggesting the model's ability to predict HY mispricing has a higher degree of uncertainty compared to IG bonds.

Table 6.6: Mispricing (%)

Metric	HY	IG	Final Sample
Mean	3.65	-0.07	1.69
Median	2.71	-0.13	0.80
Maximum	69.85	3.72	69.85
Minimum	-0.61	-3.24	-3.24
Std.Dev	5.77	0.86	4.42
n	788	881	1 669

This table provides descriptive statistics for the mispricing of the extended Merton model. It is segmented into HY, IG, and the final sample.

Figure 6.7: Histogram (Mispricing)



This figure presents a histogram of the extended Merton model mispricing. It includes HY, IG and final sample.

An alternative approach to evaluating the accuracy of the extended Merton model involves analyzing the extent to which the model explains variations in the observed credit spread. This is quantified by the adjusted R-squared in a regression output. We implement three regression models presented in table 6.7, where the dependent variable is the observed credit spread and the independent variable is the model credit spread. One for the HY sample, another for the IG sample, and lastly, a model with the final sample containing both risk grades. For HY bonds, the model exhibits an R-squared of 3.1%. For IG bonds, the R-squared is slightly lower at 1.9%. For the full sample, the R-squared shows 2.1%. These figures suggest that the Merton model is able to explain a relatively small portion of variations in observed credit spreads. 97.9% of the credit spread is left to be explained by non-default risk factors. In comparison, Eskerud (2017) found the model to explain 14.79% of the variations in credit spreads. This underscores Sæbø (2015) statement that the credit spread puzzle is highly present in the Norwegian bond market.

Table 6.7: Regression model - Degree of explanation

	Dependent variable:		
	Observed Credit Spread		
	HY	IG	Final sample
	(1)	(2)	(3)
Merton Credit Spread	-2.679^{***}	-0.140^{***}	-1.273^{***}
Constant	0.069^{***}	0.011^{***}	0.039^{***}
Adjusted R^2	0.031	0.019	0.021

Note: *p<0.1; **p<0.05; ***p<0.01

This regression output presents how much variance of the observed spread can be explained by the extended Merton mode.

6.4 Regression Analysis for HY and IG

In the attempt to solve the credit spread puzzle for Norwegian HY and IG bonds, we implement two regression outputs with respect to HY and IG. The objective is to explore the extent to which non-default-related variables can explain variation in mispricing as well as their relative magnitude. Firstly, we run a regression model (M1) with only industry dummies. The second model (M2) until model seven (M7) test each explanatory variable in conjunction with the industry dummies. Model eight (M8) is a comprehensive model containing all explanatory variables. Finally, model nine (M9) incorporates all stable and statistically significant explanatory variables. Table 6.8 and 6.9 presents the output of the regressions.

Table 6.8: HY Regression Models with Newey-West Standard Errors

	Dependent variable:								
	Mispricing								
	M1	M2	M3	M4	M5	M6	M7	M8	M9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry	−0.017***	−0.033***	−0.018***	−0.018***	−0.018***	−0.021***	−0.015***	−0.030***	−0.031***
Media									
Oil and Gas Services	0.190***	0.173***	0.190***	0.190***	0.190***	0.154	0.191***	0.145	0.173***
Pulp Paper and Forestry									
Real Estate									
Seafood	−0.029	−0.043***	−0.031***	−0.030***	−0.030***	−0.019***	−0.027***	−0.033***	−0.041***
Shipping	−0.014	−0.029***	−0.016***	−0.014***	−0.015***	−0.016***	−0.010***	−0.024***	−0.025***
Telecom IT	−0.023	0.008	−0.034***	−0.022***	−0.024***	−0.066***	−0.012***	−0.030**	0.019*
Transportation									
Market-to-book		−0.005***						−0.004***	−0.005***
Covid Dummy			0.013**					0.014***	
OSEBX				0.502*				0.120	
Oil price					−0.124*			−0.045	
Roll-spread						0.013***		0.012***	
TED-spread							3.671***	6.578***	3.738***
Constant	0.045***	0.063***	0.045***	0.045***	0.045***	0.039***	0.026***	0.021***	0.044***
Adjusted R^2	0.445	0.449	0.450	0.450	0.450	0.259	0.451	0.310	0.455
Note:									*p<0.1; **p<0.05; ***p<0.01

Table 6.9: IG Regression Models with Newey-West Standard Errors

	Dependent variable:								
	Mispricing								
	M1	M2	M3	M4	M5	M6	M7	M8	M9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry	0.005***	0.004***	0.004***	0.005***	0.004***	0.002	0.005***	0.005***	0.004***
Media	0.002	0.002	0.001	0.002*	0.002	0.001	0.003***	0.007***	0.002**
Oil and Gas Services									
Pulp Paper and Forestry	0.006***	0.006***	0.007***	0.006***	0.006***	0.009***	0.005***	0.012***	0.006***
Real Estate	0.005**	0.004***	0.004***	0.005***	0.004***	0.005***	0.005***	0.007***	0.004***
Seafood									
Shipping									
Telecom IT									
Transportation	0.014	0.014***	0.013***	0.014***	0.014***	0.005*	0.015***	0.010***	0.013***
Market-to-book		−0.0005						−0.001	
Covid Dummy			0.003**					0.009***	0.011***
OSEBX				0.011				−0.052	
Oil price					−0.049***			−0.003	
Roll-spread						0.006***		0.005***	
TED-Spread							1.379***	2.698***	2.925***
Constant	−0.005***	−0.004*	−0.006***	−0.005***	−0.005***	−0.007***	−0.010***	−0.022***	−0.018***
Adjusted R^2	0.124	0.124	0.152	0.123	0.166	0.073	0.239	0.432	0.475
Note:									*p<0.1; **p<0.05; ***p<0.01

6.4.1 Industry

For HY bonds, industry seems to be an important explanatory factor, explaining 44.5% of the mispricing variance. Initially, only industry and oil and gas services are statistically significant. The negative coefficient for industry suggests that exposure to this sector is associated with lower mispricing. For oil and gas services, the coefficient is positive, suggesting that exposure to this sector is associated with higher mispricing. In the cases of shipping, telecom IT, and seafood, the coefficients are negative and non-significant. One possible explanation for the non-significant coefficient for shipping could be due to its strong negative correlation with industry (see table D.1). This can indicate that effects typically attributed to the shipping sector are captured by the industry dummy.

Additionally, the non-significant coefficients for seafood and telecom IT could be due to the small sample size. Both sectors have only one distinct bond, and consequently few observations.

The explanatory power of industry dummies is prominent for IG bonds but relatively lower compared to HY bonds. It explains 12.4% of the variance. Industry, pulp, paper and forestry, and real estate have significant positive coefficients. This suggests that exposure to these industries is associated with higher mispricing. Media and transportation do not exhibit significant coefficients.

The introduction of additional explanatory variables in the subsequent models leads to a shift in significance for the sectors that initially yielded non-significant coefficients (except media across most models). This could be due to a small sample size or the presence of intercorrelation among variables. Such intercorrelations can cause some of the variability explained by the industry dummies to be captured by new variables.

Overall, our findings for industry align with Sæbø (2011). This highlights the importance of industry as a determinant of mispricing. These findings suggest there are different risk perceptions and market dynamics between the risk grades. HY bonds appear more sensitive to industry-specific risk explained by a greater coefficient compared to IG bonds. Our findings also suggest that most HY industries are associated with lower mispricing. This implies that exposure to certain industries results in a larger portion of mispricing being attributed to default risk. This aligns with the risk profile of HY bonds. Conversely, IG bonds have an inverse relationship, with all industries having a positive coefficient. This suggests that exposure to those industries is associated with higher mispricing.

6.4.2 Market-to-book

The market-to-book ratio consistently yields statistically significant negative coefficients across all models for HY bonds. This indicates that firms with higher market-to-book ratios are associated with lower mispricing. This is expected, considering that higher market-to-book firms are associated with more uncertainty. Reduced mispricing implies that a greater portion of mispricing can be attributed to default risk. Therefore, we find this relationship to be reasonable. The market-to-book ratio also enhanced the adjusted R-squared by 0.5%. These findings are in line with Eskerud (2017).

For IG bonds, there is no evident relationship between mispricing and the market-to-book ratio. Despite indicating a similar negative relationship as HY, the coefficient is consistently non-significant. Additionally, this variable does not enhance the adjusted R-squared. The findings for IG bonds are more in line with Sæbø (2011). He concluded no significant relationship for both risk grades.

6.4.3 Covid-19

The covid-19 dummy, indicates that the pandemic made a statistically significant impact on mispricing. We find that both risk grades are associated with increased mispricing post-pandemic. The variable enhanced the adjusted R-squared for HY bonds by 0.5% and 2.8% for IG bonds.

However, these findings partly contradict the data presented in table A.3 and A.4. These tables indicate that mispricing for IG bonds is higher post-pandemic compared to pre-pandemic. This aligns with the regression output on IG. Conversely, post-pandemic mispricing for HY bonds is lower compared to pre-pandemic, contradicting findings in the regression. The exact cause of the discrepancy is unclear and could stem from a variety of reasons. A possible explanation for the lower mispricing post-pandemic can be an attribute of increased default risk. This stems from the operational and financial difficulties a pandemic poses. This is particularly relevant for HY bonds, which are inherently riskier. Conversely, mispricing for IG bonds rose, suggesting that other factors than default risk affects safer securities post-pandemic.

Another plausible explanation for reduced mispricing post-pandemic for HY bonds can be an attribute of increase in market participation. A surge in market participation can lead to greater market efficiency, especially given the traditional illiquid nature of the Norwegian bond market. As market efficiency improves, one can expect other risk factors, such as liquidity, to be less present. Consequently, causing observed credit spreads and subsequently mispricing to fall.

Additionally, the deviating results for HY bonds between observed mispricing and regression results could stem from a time-lag effect in the data. Specifically, that the regression model has a harder time capturing the actual market dynamics post-pandemic for HY bonds compared to IG bonds. Furthermore, quantitative easing (QE) by the

Norwegian central bank impacts bond pricing. This results in higher bond prices and subsequently lower mispricing.

6.4.4 OSEBX

Consistent with findings of Sæbø (2011), our analysis reveals no significant relationship between excess return on OSEBX and mispricing for both risk grades. This can be an attribute of equity price changes reflecting default rates (Sæbø, 2011). This implies that higher equity prices result in lower expected default rates, consequently, reducing credit risk. Another explanation can be that bonds are associated with firm-specific credit risk rather than broad market credit risk. Assuming the Merton model effectively captures firm-specific credit risk, excess return on OSEBX should not provide additional information on bond pricing.

Furthermore, the presence of institutional investors like pension funds in the Norwegian bond market[7] can also affect the relevance of this variable. Pension funds may have investment mandates that are not directly tied to equity market performance. Hence, fewer trades are executed as a direct consequence of changes in the equity market. This implies that the presence of institutional investors could further explain why OSEBX is not a relevant explanatory variable.

6.4.5 Oil Price

Similar to Sæbø (2011), our analysis indicates that oil price is a non-relevant variable in explaining mispricing. For HY bonds, the oil price does improve the adjusted R-squared by 0.5%, notably with an initial negative significant coefficient at 90% confidence interval. This suggests that higher oil price results in lower mispricing. Interestingly, the oil price has a low correlation with sectors that are known as oil-dependent such as Shipping. This can imply that the effect of oil price has a complex relationship with mispricing. A possible explanation could be that oil price is indirectly captured through the default risk component as a firm-specific risk. Another possible explanation could be that the effect of oil price is inherently integrated into the industry dummies. However, the introduction of other variables results in an unstable coefficient, making it hard to draw solid inferences.

[7] As of the end of 2020, pension funds alone accounted for 17% of the invested capital in the Norwegian bond market (Bank, 2022).

For IG bonds, oil price initially yields a statistically significant coefficient, and enhances the adjusted R squared by 4.4%. Similar to HY bonds, the introduction of other variables results in the variable being insignificant. Due to its unstable behavior, it is hard to draw any solid inference.

6.4.6 Roll-spread

The Roll-spread yields ambiguous findings for both risk grades. This challenges existing literature like Riis-Johansen and Kronberg (2021), which found liquidity to play a pivotal role in explaining credit spread[8] variations. Both risk grades show statistically significant coefficients across all models. However, it reduces the model's adjusted R-squared by 18.6% for HY bonds and 5.3% for IG bonds. Despite its statistical significance, the reduced adjusted R-squared makes it challenging to draw solid inferences. It is noteworthy that for the HY sample, the Roll-spread appears to correlate with the covid-19 dummy, market-to-book ratio, and telecom IT sector.[9] This suggests that liquidity risk is already incorporated into those variables. In contrast, such correlations are not evident for the IG sample.[10]

Our results deviate from Riis-Johansen and Kronberg (2021) and our intuition. This leads us to scrutinize the inherent limitations of the roll measure. Particularly its inability to capture all dimensions of liquidity, such as trading volume and transaction costs. Additionally, as we use theoretical price data rather than actual price data, we believe this could disturb the effectiveness of the variable. Consequently, the interpretation of the Roll-spread results should be approached with caution.

6.4.7 TED-spread

The TED-spread demonstrates a significant positive relationship with mispricing, further enhancing the adjusted R-squared for both risk grades. The HY model adjusted R-squared improves by 0.6% and the IG model by 11.5%. These findings suggest that increased market risk is associated with higher mispricing for both risk grades. Interestingly, the magnitude of the coefficient for HY bonds is greater than that of IG.

[8]Riis-Johansen and Kronberg (2021) defined credit spread as the difference in yield to maturity of a bond and NIBOR 3M

[9]See figure D.1

[10]See figure D.2

This indicates that market risk has a stronger influence on riskier bonds. This is not surprising, as HY issuers are often associated with being more sensitive to changes in market conditions.

6.4.8 Summary

This part of the analysis explores the impact different non-default related variables have on mispricing. Both in terms of relative magnitude and explanatory power. We find that the industry issuers operate in is an important variable explaining the variance in mispricing for both risk grades. However, the risk grades exhibit distinct risk perceptions and market dynamics. HY bonds appear to be more sensitive to industry exposure. Most industry dummies reveal a negative relationship with a greater coefficient compared to IG bonds. Conversely, IG bonds have a positive relationship between mispricing and industry, with a less pronounced effect. Furthermore, we find the market-to-book ratio for HY bonds to have a negative impact on mispricing. For IG bonds, there is no evident relationship. Additionally, the covid-19 dummy suggests that the pandemic has an impact on mispricing for both risk grades. Notably, our findings for HY contradict the observed mispricing, making it hard to draw solid inferences. For safer securities, we find a significant positive relationship. This suggests that mispricing for IG bonds increases post-pandemic. Lastly, the TED-spread yields a significant positive relationship for both risk grades. Both risk grades show the same relationship, suggesting that increased market risk results in increased mispricing. Granted, the magnitude is greatest for HY bonds. When including all stable and significant variables, the model explains 45.5% of the variance in mispricing for HY bonds and 47.5% for IG bonds. Leaving the rest unexplained as a part of the credit spread puzzle.

6.5 Isolated Difference Regression

Part one of the regression analysis investigates HY and IG mispricing separately. The objective of this analysis is to isolate the difference in credit spread between HY and IG and investigate the drivers of the difference. As mentioned in section 5.5 the difference in observed credit spread between HY and IG is the dependent variable. The first model (M1) throughout the eighth model (M8) incorporates regression models with only one explanatory variable. Model nine (M9) includes all explanatory variables. Lastly, model ten (M10) includes all stable and statistically significant variables.

Table 6.10: Regression Models with Newey-West Standard Errors

	Dependent variable:									
	Mean Credit Spread Difference									
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Coupon	−0.017								−0.221	
Maturity		−0.013**							0.002	
Leverage			0.004***						0.004***	0.004***
Asset Volatility				−0.143***					−0.037*	
OSEBX					0.314				0.189	
Oil price						−0.001***			−0.0002**	
Ted spread							4.639***		−0.698	
Credit risk								−0.0001***	−0.00000	
Constant	0.034	0.021***	0.015***	0.024***	0.070***	0.034***	0.016***	0.034***	0.038**	0.015***
Adjusted R^2	-0.011	0.124	0.836	0.278	0.250	0.008	0.173	-0.006	0.860	0.836

Note: *p<0.1; **p<0.05; ***p<0.01

6.5.1 Coupon

The difference in coupon rate has a negative coefficient of -0.017. This indicates a unit increase in the average difference leads to a 1.7% reduction in the credit spread difference. All things equal, higher coupon rates entail a higher bond price. Consequently, it is reasonable for an increase in the average difference in coupon rate to have a decreasing effect on the credit spread difference between IG and HY. Additionally, with an adjusted R-squared of -1.1% the variable has a low degree of explanation. The result suggests that the difference in coupon rate does not determine the difference in credit spread, ceteris paribus.

6.5.2 Maturity

The difference in maturity is included to capture potential bias when comparing bonds with different maturities. It has a coefficient of -0.013 on its own, which indicates a unit increase in maturity difference leads to a 1.3% decrease in credit spread difference.

However, the effect is insignificant and unstable once other variables are included. Landschoot (2004) finds that credit spreads for bonds with lower ratings and longer maturities tend to be more sensitive to macroeconomic changes than bonds with higher ratings and shorter maturities. Consequently, one would expect an increase in the maturity difference between HY and IG would lead to an increased credit spread. However, this relationship is unstable as the estimator changes sign and takes a value of 0.002 once other variables are included. It is therefore difficult to draw any consequential inference.

6.5.3 Leverage

Difference in leverage is an influential factor in explaining the difference in observed spread between IG and HY. Leverage is able to explain 83.6% of the variance in credit spread differences. Additionally, the coefficient shows a value of 0.004. One unit increase in the leverage difference leads to a 0.4% increase in the credit spread difference. The coefficient is stable and significant across all models. As table 6.5 shows, HY bonds are, on average, considerably more leveraged than IG bonds. Consequently, an increase in leverage difference is associated with HY bonds having increased risk relative to IG bonds. Such a relationship causes the credit spread difference to widen, as the model predicts.

6.5.4 Asset Volatility

The coefficient is -0.143 and significant in a model on its own. This means a unit increase in the asset volatility difference leads to a 14.3% decrease in the credit spread difference. However, this relationship is stripped away once other variables are introduced into the model. The coefficient is further reduced to -0.037 and is no longer statistically significant. This relationship is somewhat surprising, considering increased asset volatility usually entails a higher probability that the asset value falls below the default barrier. Hence, one would expect a positive coefficient. However, our deviating results from this intuition could be a consequence of IG having higher average asset volatility compared to HY. As table 6.5 shows, our sample indicates that IG bonds on average have higher asset volatility compared to HY bonds. Following the intuition that safer securities are associated with lower asset volatility, this could indicate that the model assumes IG bonds to be more risky. Therefore, this leads to results deviating from the economic intuition that an increase in asset volatility difference leads to credit spread difference widening. Nonetheless, the coefficient is unstable and non-significant. Therefore, it is difficult to draw a solid inference.

6.5.5 OSEBX

Excess return on the OSEBX seems to have a great effect on credit spread difference, with a coefficient of 0.31 and 0.19 when other variables are included. However, none of the coefficients are statistically significant. This means the change in excess return in OSEBX has no significant effect on the credit spread difference between IG and HY. The accuracy given by adjusted R-squared is also low, with a value of 0.8%. This result is in line with the findings in section 6.4 where excess return on OSEBX has no effect on mispricing for either HY or IG.

6.5.6 Oil Price

The change in oil prices has a coefficient of -0.001. This means a unit increase in oil prices leads to a 0.1% decrease in the credit spread difference between HY and IG. The variable is able to explain 25% of the variance in the credit spread difference. This effect is initially statistically significant in the model on its own, but the introduction of other variables affects its significance. Notably, the economic magnitude given by the coefficient decreases to -0.0002 when other variables are introduced. The negative sign of the coefficient can be in relation to HY being predominantly oil dependent firms. As the oil price increases, the perceived risk in the sector decreases, leading to a lower credit spread. The relatively low economic magnitude is surprising, as almost 49% of the sample operates within oil related sectors. However, only three percent operates directly in the oil and gas sector, which can explain the low economic magnitude.

6.5.7 TED-spread

The TED-spread initially has a large effect on the credit spread difference. It has a statistically significant coefficient of 4.639. This indicates that increased turmoil in the general market leads to an increased difference in credit spread. However, when introducing other variables, the coefficient changes sign and becomes insignificant. The variable is able to explain 17.3% of the variation. However, due to its unstable behavior, one cannot draw meaningful inferences from this variable.

6.5.8 Credit Risk

The credit risk is given by the difference in the proportion of credit spread that is explained by default risk with respect to HY and IG. It seems to have an insignificant role in determining the difference in credit spreads. The coefficient initially shows a value of -0.0001, which is statistically significant. However, with the introduction of other variables, the coefficient diminishes and is no longer significant. The adjusted R-squared is -0.6% which indicates that the model has low accuracy. This is in line with findings from section 6.3 where the Merton model struggles to capture credit risk accurately.

6.5.9 Summary

In this part of the analysis, we quantify the dynamics that influence the credit spread difference between HY and IG. We find leverage to be an important factor, as it explains 83.6% of the variance as well as being statistically significant. Other factors, particularly asset volatility, oil price, TED spread, and credit risk, initially yield statistically significant coefficients. However, once other factors are included, the variables are no longer significant. Consequently, one cannot draw any inferences. This can be due to potential bias. Employing a time series approach, where average firm variables per risk grade at a given time are utilized, can introduce biases. Feldhütter and Schaefer (2018), as cited by Sæbø (2015), argues that utilizing such average (per rating) analysis can lead to a convexity bias. Meaning, you run the risk of masking the fundamental variability of individual firms.

7 Robustness test

From previous research, we observe that asset volatility and interest rate modelling are crucial components of the model. Correia et al. (2017), for instance, argues that asset volatility is the most important variable determining default risk. Furthermore, term structure modelling such as the Nelson-Siegel model can introduce errors when used to model risk-free rates (Eom et al., 2004). Consequently, we conduct a sensitivity analysis to test the robustness of these variables. We apply the mean absolute deviation (MAD) as shown in equation 7.1. This sensitivity analysis measures, in absolute values, the average magnitude of errors in mispricing with regard to changes in a given variable.

$$MAD = \sum \frac{|Observed\ spread_{i,t} - Model\ spread_{i,t}|}{n} \tag{7.1}$$

7.1 Asset Volatility

Table 6.5 illustrates that IG bonds, which are widely known as the safest asset of the two risk grades, have the highest asset volatility. Due to peculiar results, especially for IG bonds, we perform the MAD sensitivity analysis with increments of +/- 5% to see how it affects mispricing. Table 7.1 reveals that mispricing is not sensitive to changes in asset volatility. This is surprising considering asset volatility is acknowledged to be the most important variable determining default risk (Correia et al., 2017).

However, we find that the model's performance at the current implemented volatility level is suboptimal. For HY, we see that a decrease in asset volatility consistently reduces model performance. Conversely, an increase in asset volatility consequently improves the model's performance. For IG, we see a similar relationship when reducing asset volatility. However, the relationship to increased asset volatility is less clear. The model's performance improves up to a 40% increase in asset volatility from the current level. Implementing any higher than a 40% increase results in reduced model performance.

Table 7.1: Mean absolute deviation (bps) - Asset volatility

	HY	IG
$\sigma_V - 50\%$	199.77	192.13
$\sigma_V - 45\%$	199.76	192.13
$\sigma_V - 40\%$	199.74	192.12
$\sigma_V - 35\%$	199.72	192.11
$\sigma_V - 30\%$	199.70	192.09
$\sigma_V - 25\%$	199.67	192.05
$\sigma_V - 20\%$	199.64	192.01
$\sigma_V - 15\%$	199.61	191.95
$\sigma_V - 10\%$	199.58	191.89
$\sigma_V - 5\%$	199.54	191.83
σ_V	199.49	191.75
$\sigma_V + 5\%$	199.44	191.67
$\sigma_V + 10\%$	199.41	191.59
$\sigma_V + 15\%$	199.38	191.50
$\sigma_V + 20\%$	199.35	191.40
$\sigma_V + 25\%$	199.31	191.32
$\sigma_V + 30\%$	199.28	191.26
$\sigma_V + 35\%$	199.24	191.22
$\sigma_V + 40\%$	199.19	191.22
$\sigma_V + 45\%$	199.14	191.26
$\sigma_V + 50\%$	199.09	191.34

This table shows the sensitivity of mispricing to changes in asset volatility. Changes in asset volatility on the left side and corresponding changes in mispricing on the right side. The scenarios range from decrease of 50% and increase of 50% in asset volatility.

7.2 Interest Rate

Table 7.2 demonstrates that mispricing is sensitive to fluctuations in interest rates, with notable differences between HY and IG bonds. For HY bonds, a decrease in interest rates results in a greater magnitude of errors, indicating weaker model performance. Conversely, increased interest rates suggest the model's performance improves as the magnitude of errors decreases.

However, the relationship between IG bonds and interest rates is more complex. A reduction in interest rates initially enhances the model's accuracy, whereas a reduction of 15% results in the lowest magnitude of errors. When interest rates are decreased below 15%, the model's performance starts deteriorating. Additionally, increased interest rates, in contrast to HY bonds, result in a higher magnitude of errors, implying poorer performance.

These findings lead us to conclude that HY model performs best when interest rates are high. For IG, the relationship is less clear, as both an increase and a decrease seem to negatively affect model performance.

Table 7.2: Mean absolute deviation (bps) - Interest rates

	HY	IG
$r - 50\%$	454.12	93.99
$r - 45\%$	445.25	85.02
$r - 40\%$	436.36	76.81
$r - 35\%$	427.49	69.48
$r - 30\%$	418.62	63.27
$r - 25\%$	409.75	58.51
$r - 20\%$	400.87	55.11
$r - 15\%$	391.99	53.52
$r - 10\%$	383.17	53.94
$r - 5\%$	374.37	56.56
r	365.64	60.98
$r + 5\%$	357.00	66.67
$r + 10\%$	348.49	73.52
$r + 15\%$	340.16	81.02
$r + 20\%$	332.09	88.89
$r + 25\%$	324.41	97.03
$r + 30\%$	317.12	105.37
$r + 35\%$	310.18	113.91
$r + 40\%$	303.85	122.59
$r + 45\%$	298.04	131.38
$r + 50\%$	292.58	140.27

This table shows the sensitivity of mispricing to changes in interest rate. Changes in interest rate on the left side and corresponding changes in mispricing on the right side. The scenarios range from decrease of 50% and increase of 50% in interest rate.

8 Conclusion

The main objective of this thesis is to uncover and explain differences in mispricing between HY and IG corporate bonds in the Norwegian bond market. Our focus extends to both the relative magnitude of mispricing and its explanatory power. Additionally, our analysis extends to predicting credit spread differences between these risk grades. The analysis covers data spanning the period 2014–2022. Employing the Extended Merton model, we calculate theoretical credit spreads and compare them with the observed credit spread. In this thesis, we concentrate on three categories of risk compensation: default risk, liquidity risk, and market risk.

Similar to previous research, such as Eom et al. (2004) and Ytterdal and Knappskog (2015), we find that the extended Merton model, on average, underpredicts spreads for HY bonds. In contrast, the model overpredicts spreads for IG bonds, which contradicts the findings of Eom et al. (2004). Furthermore, default-related risks explain a small portion of the variance in observed spreads, namely 3.1% for HY and 1.9% for IG bonds. This is unexpectedly low compared to former research such as Sæbø (2011) and Eskerud (2017). They find default risk for Norwegian corporate bonds to account for 21.5% and 14.79% of the variance in spreads. Although our findings deviate in magnitude compared to former research, we observe that default-related risk can explain a greater portion of the variance in observed spread for HY bonds compared to IG bonds. This aligns with the understanding that safer bonds are less influenced by default risk.

Utilizing a multivariate OLS regression model, we explore the disparities in mispricing, both their relative magnitude and the explanatory power of HY and IG bonds. Similar to Sæbø (2011), we discover that the industries the issuer operates in play an important role in explaining mispricing for both risk grades. Notably, with a higher explanatory power for HY bonds compared to IG bonds. This is likely due to the HY samples exposure to industries associated with a higher degree of cyclical behavior. We observe that mispricing for HY bonds has a negative relationship to industry, whereas the relationship for IG bonds is inverse. Additionally, the magnitude of the coefficients is greater for HY compared to IG.

Our findings for market-to-book partly deviate from the findings of Sæbø (2011). He finds market-to-book to have no significant relationship with mispricing for both risk grades. Our finding, similar to Ytterdal and Knappskog (2015) suggests HY bonds and market-to-book ratio to have a significant negative relationship with mispricing. Conversely, our findings for IG bonds suggest there is no evident relationship.

The covid-19 dummy's' impact on mispricing yields contradicting results for HY bonds. The regression model indicates an increase in mispricing post-pandemic for both risk grades, with a greater magnitude for HY bonds compared to IG. However, we observe mispricing for HY bonds to fall post-pandemic. Despite contradictory findings for HY bonds, there seems to be a significant positive relationship between IG bonds and covid-19. The mispricing increases post-pandemic. Additionally, the TED spread plays a significant role for both risk grades, with a more pronounced impact on HY bonds.

Combining all stable and significant variables, we are able to explain 45.5% of the variation in mispricing for HY bonds and 47.5% for IG bonds. This leaves 54.5% and 52.5% of the credit spread unexplained, highlighting the presence of a credit spread puzzle in the Norwegian bond market. In summary, while similar factors influence mispricing for both risk grades, their impact varies in magnitude, with HY mispricing being more sensitive to industry dynamics and market risk.

Furthermore, we conduct a regression analysis of the credit spread differences between HY and IG bonds. The goal of this analysis is to predict the determinants of credit spread differences and quantify their effects. The model predicts that the difference in average coupon rate and maturity between the two risk grades has no significant effect. We find leverage to be significant and able to explain 83.6% of the variance in the difference in credit spread between the two risk grades. This suggests that a large portion of the variance can be explained by the difference in issuers financial risks. Additional variables tested are TED-spread, oil price, OSEBX, and credit risk. None of these variables shows a significant relationship, thus being deemed non-relevant variables in explaining credit spread differences.

Lastly, we perform a robustness test. Calculating the mean absolute deviation of mispricing with regard to changes in asset volatility and interest rates. We uncover how sensitive mispricing is to changes in these variables. Changes in asset volatility do not impact model performance significantly. However, we observe a relationship for HY, indicating that increased volatility improves model accuracy. For IG, we observe the same relationship when reducing asset volatility. However, increased asset volatility improves the model performance up to a 40% increase. Asset volatilities above this level result in reduced performance. Furthermore, we find mispricing to be sensitive to changes in interest rates. For HY, increased interest rates improves the model's performance. For IG, we find a less clear relationship. Both an increase and a decrease affect the model in a negative manner. Notably, the model performs best when interest rates are 15% lower than the implemented interest rate levels.

8.1 Limitations and Future Research

8.1.1 Limitations

One of the primary challenges in writing this thesis was time constraints. Data collection proved to be exhaustive and time-consuming, especially given the diversity of data sources and the need for manual data mining for financial, equity, and interest rate data. Furthermore, aligning data from various data sources introduced uncertainties that could lead to measurement errors. The selection, understanding, and implementation of the theoretical framework also demanded a significant amount of time.

Our study is constrained by a relatively small sample size, which could potentially impact the robustness and generalizability of our findings. Given these constraints, we were unable to perform out-of-sample testing. Therefore, the validity and generalizability of our results should be interpreted with caution.

8.1.2 Future Research

Several avenues for future research arise from this thesis. Firstly, employing varying recovery rates across industries and risk grades is interesting. Eskerud (2017) finds the model to be sensitive to changes in recovery rates. Therefore, implementing a static uniform recovery rate across all observations can yield an incorrect reflection of the real-world recovery rate dynamics. We acknowledge that the incorporation of dynamic recovery rates can enhance the accuracy of the extended Merton model.

Another avenue for future research is the utilization of an alternative equity volatility measure. Using more sophisticated equity volatility measures such as ARCH, GARCH, or bond implied volatility can provide interesting insight as it offers a more nuanced understanding of volatility. Despite findings from table 7.1 indicating that asset volatility does not have a huge impact on mispricing, we still find this avenue for future research to be interesting. This is emphasized by Correia et al. (2017), suggesting asset volatility to be an important variable, as well as Eom et al. (2004) finding that the use of bond implied volatility yields a lower predicted error.

Considering contradicting findings regarding liquidity compared to literature like Riis-Johansen and Kronberg (2021), future research can benefit from employing a different liquidity measure. Including actual trading volumes and/or bid-ask spreads can provide interesting insights into liquidity.

References

Afik, Z., Arad, O., & Galil, K. (2012). Using merton model: An empirical assessment of alternatives. (1202).

Bank, N. (2022). *Det norske finansielle systemet 2022* (Norges Bank Report No. ISSN 2535-3993). Norges Bank. https://www.norges-bank.no/aktuelt/nyheter-og-hendelser/Publikasjoner/det-norske-finansielle-systemet/2022-dnfs/innhold/

Berg, P. (2022). *Predicating the credit spread difference between nordic and european high-yield.*

Black, F., & Cox, J. C. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *The Journal of Finance*, *31*(2), 351–367.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637–654.

Bodie, Z., Kane, A., & Marcus, A. J. (2018). *Investments.* McGraw-Hill Education.

CFI. (n.d.). *Heteroskedasticity.* https://corporatefinanceinstitute.com/resources/data-science/heteroskedasticity/

Collin-Dufresne, P., & Goldstein, R. S. (2001). Do credit spreads reflect stationary leverage ratios? *The Journal of Finance*, *56*(5), 1929–1957.

Correia, M., Kang, J., & Richardson, S. (2017). Asset volatility. *Review of Accounting Studies.*

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, *67*(2), 719–760.

Crosbie, P., & Bohn, J. (2003). *Modeling default risk.* https://www.moodysanalytics.com/-/media/whitepaper/before-2011/12-18-03-modeling-default-risk.pdf

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *The Journal of Finance*, *56*(1), 247–277.

Eom, Y. H., Helwege, J., & Huang, J.-Z. (2004). Structural models of corporate bond pricing: An empirical analysis. *The Review of Financial Studies*, *17*(2), 499–544.

Eskerud, H. (2017). *Predicting credit spreads in the norwegian corporate bonds market.*

Feldhütter, P., & Schaefer, S. M. (2018). The myth of the credit spread puzzle. *The Review of Financial Studies*, *31*(8), 2897–2942.

Fidelity. (2023). *Bond ratings.* https://www.fidelity.com/learning-center/investment-products/fixed-income-bonds/bond-ratings

Frafjord, J. (2020). *Spår ratingrush i industriobligasjoner.* https://www.finansavisen.no/nyheter/finans/2020/06/29/7541811/spar-ratingrush-i-industriobligasjoner

Geske, R. (1979). The valuation of compound options. *Journal of Financial Economics*, *7*(1), 63–81.

Grace-Martin, K. (n.d.). *Anatomy of a normal probability plot.* https://www.theanalysisfactor.com/anatomy-of-a-normal-probability-plot/

Harris, L. (1990). Statistical properties of the roll serial covariance bid/ask spread estimator. *The Journal of Finance*, *45*(2), 579–590.

Hayes, A. (2022). *Shadow rating: What it means, how it works.* https://www.investopedia.com/terms/s/shadowrating.asp

Jarrow, R. A. (2011). Credit market equilibrium theory and evidence: Revisiting the structural versus reduced form credit risk model debate. *Finance Research Letters*, *8*(1), 2–7.

Jarrow, R. A., & Turnbull, S. M. (1995). Pricing derivatives on financial securities subject to credit risk. *The Journal of Finance*, *50*(1), 53–85.

Keenan, S. C., Shtogrin, I., & Sobehart, J. (1999). Historical default rates of corporate bond issuers, 1920 - 1998. *Moody's Investors Service.*

LaMorte, W. W. (2016). *Central limit theorem.* https://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_probability/BS704_Probability12.html

Landschoot, A. V. (2004). The Determinants of Credit Spreads. *Financial Stability Review*, *2*(1), 135–155. https://ideas.repec.org/a/nbb/fsrart/v2y2004i1p135-155.html

Leland, H. E. (1994). Corporate debt value, bond covenants, and optimal capital structure. *The Journal of Finance*, *49*(4), 1213–1252.

Leland, H. E., & Toft, K. B. (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *The Journal of Finance*, *51*(3), 987–1019.

Longstaff, F. A., & Schwartz, E. S. (1995). A simple approach to valuing risky fixed and floating rate debt. *The Journal of Finance*, *50*(3), 789–819.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Neely, M. C. (1997). *The name is bond—indexed bond.* https://www.stlouisfed.org/publications/regional-economist/january-1997/the-name-is-bondindexed-bond

Nelson, C. R., & Siegel, A. F. (1987). Parsimonious modeling of yield curves. *The Journal of Business*, *60*(4), 473–489.

Nordic Bond Pricing. (2023). Nordic bond pricing - valuation methodologies used in conjunction with evaluated pricing for nordic bond issues [Internal document, Nordic Bond Pricing, 11.09.23].

Riis-Johansen, E., & Kronberg, J. A. (2021). *Estimating the liquidity premium in the norwegian high yield bond market.*

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance*, *39*(4), 1127–1139.

Sæbø, J. K. (2011). Risikopremier i norsk kreditt. *Praktisk økonomi & finans*, *27*(1), 99–108.

Sæbø, J. K. (2015). The credit spread puzzle does exist– but is it really a puzzle? *The Journal of Fixed Income*, *25*(1), 75–83.

Schestag, R., Schuster, P., & Uhrig-Homburg, M. (2016). Measuring liquidity in bond markets. *The Review of Financial Studies*, *29*(5), 1170–1219.

SEC. (2023). *Bonds.* https://www.investor.gov/introduction-investing/investing-basics/investment-products/bonds-or-fixed-income-products/bonds

Shweta. (2021). *The intuition behind the assumptions of linear regression algorithm.* https://towardsdatascience.com/linear-regression-assumptions-why-is-it-important-af28438a44a1

Smith, T. (2023). *Autocorrelation: What it is, how it works, tests.* https://www.investopedia.com/terms/a/autocorrelation.asp

Solutions, S. (2013). *Normality.* https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/normality/

Sønnervik, K. (2017). Forbud mot skyggerating kan begrense kapitaltilgangen for norske selskaper. *Idunn.*

Sundaresan, S. (2013). A review of merton's model of the firm's capital structure with its wide applications. *Annual Review of Financial Economics*, *5*(1), 21–41.

Taylor, J. B., & Williams, J. C. (2009). A black swan in the money market. *American Economic Journal: Macroeconomics*, *1*(1), 58–83.

Tuovila, A. (2023). *Capital structure definition, types, importance, and examples*. https://www.investopedia.com/terms/c/capitalstructure.asp

Vipond, T. (2023). *Debt vs equity financing*. https://corporatefinanceinstitute.com/resources/commercial-lending/debt-vs-equity/

Wang, Y. (2009). Structural credit risk modeling: Merton and beyond. *Risk Management*, (16), 30–33.

Ytterdal, A. G., & Knappskog, B. H. (2015). *Predicting spreads in the nordic high yield bonds market*.

Appendices

A Descriptive Statistics

Table A.1: HY bond sample by industries

Industry	n	Percentage	Observations	Percentage
Shipping	9	50	391	50
Industry	4	22	213	27
Transportation	2	11	60	8
Oil and Gas Services	1	6	28	4
Seafood	1	6	66	8
Telecom IT	1	6	30	4
Total	18	100	788	100

This table presents a breakdown of the final sample for HY bonds. It presents the number of distinct bonds (n) issued within each industry and their corresponding percentage of the total sample. Additionally, it shows the number of price observations for each sector and their corresponding percentage of the total sample.

Table A.2: IG bond sample by industries

Industry	n	Percentage	Observations	Percentage
Real Estate	6	32	312	35
Industry	4	21	213	24
Media	4	21	112	13
Convenience Goods	2	10	126	14
Pulp Paper and Forestry	2	10	65	7
Transportation	1	5	53	6
Total	19	100	881	100

This table presents a breakdown of the final sample for IG bonds. It presents the number of distinct bonds (n) issued within each industry and their corresponding percentage of the total sample. Additionally, it shows the number of price observations for each sector and their corresponding percentage of the total sample.

Table A.3: Mispricing - HY

Metric	Pre-Covid	Post-Covid
Mean	3.66	3.62
Median	2.73	2.69
Maximum	69.85	13.19
Minimum	-0.19	-0.61
Std. Dev	6.13	2.83

This table presents descriptive statistics for the HY bond sample with regards to mispricing pre and post-Covid-19.

Table A.4: Mispricing - IG

Metric	Pre-Covid	Post-Covid
Mean	-0.18	0.15
Median	-0.20	0.23
Maximum	1.45	3.72
Minimum	-1.72	-3.24
Std. Dev	0.49	1.26

This table presents descriptive statistics for the IG bond sample with regards to mispricing pre and post-Covid-19.

B Breusch-Pagan Test

These tables display the result of a Breusch-Pagan test for our respective models. The test's key outputs are the BP statistic and the corresponding P-value. A significant BP statistic given by a P-value less than 0.05 indicates the presence of heteroscedasticity. If the P-value is greater than 0.05, it indicates the presence of homoscedasticity.

Table B.1: Breusch-Pagan Test Results for HY Model

Test	BP Statistic	df	P-Value
Breusch-Pagan	209.34	11.00	0.00

Table B.2: Breusch-Pagan Test Results for IG Model

Test	BP Statistic	df	P-Value
Breusch-Pagan	135.69	11.00	0.00

Table B.3: Breusch-Pagan Test Results for (HY - IG) Model

Test	BP Statistic	df	P-Value
Breusch-Pagan	30.70	8.00	0.00

C Variance Inflation Factor (VIF)

These tables display the variance inflation factor (VIF) which is a test conducted to identify multicollinearity among variables. The general rule of thumb is that a VIF greater than 10 indicates multicollinearity.

Table C.1: Variance Inflation Factors for HY Model

Variable	VIF
Industry	8.05
Oil and Gas Services	1.27
Seafood	1.14
Shipping	8.39
Telecom IT	7.00
Market-to-book	9.08
Covid Dummy	2.08
OSEBX	1.01
Oil price	1.06
Roll Spread	2.97
TED-Spread	1.75

Table C.2: Variance Inflation Factors for IG Model

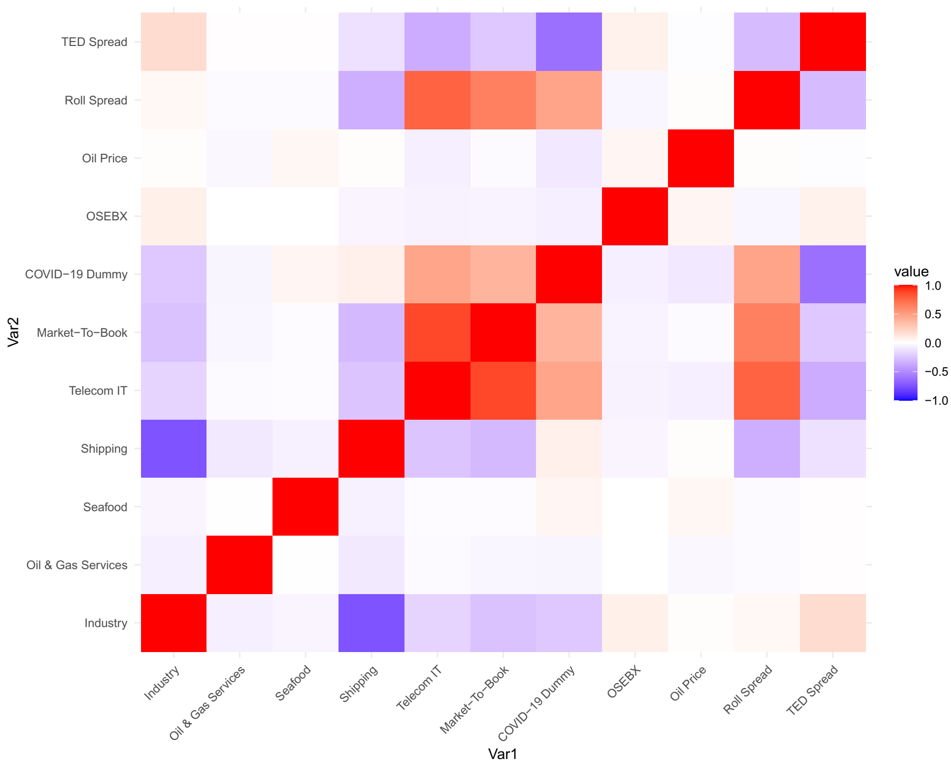
Variable	VIF
Convenience Goods	1.06
Industry	1.53
Media	2.69
Pulp Paper and Forestry	1.51
Transportation	1.16
Market-to-book	2.66
Covid Dummy	1.89
OSEBX	1.07
Oil Price	1.07
Roll Spread	1.53
TED-Spread	1.96

Table C.3: Variance Inflation Factors for (HY - IG) model

Variable	VIF
Coupon	2.50
Maturity	1.65
Leverage	2.18
Asset Volatility	3.28
Oil price	1.57
OSEBX	1.07
Ted-spread	2.30
Credit risk	1.07

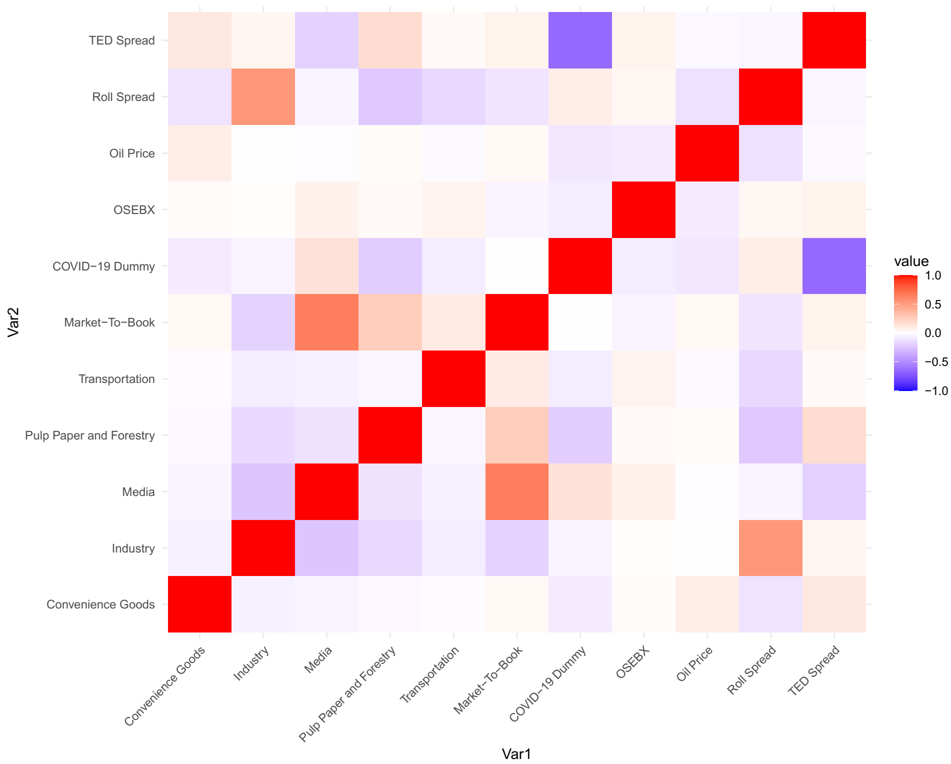
D Correlation Matrices

Figure D.1: Correlation matrix HY



This figure presents a correlation matrix for independent variables for HY. Bright red indicates perfect correlation, while bright blue indicates perfect negative correlation.

Figure D.2: Correlation matrix IG



This figure presents a correlation matrix for independent variables for IG. Bright red indicates perfect correlation, while bright blue indicates perfect negative correlation.

E Measure of Tendency and Variability

The figures below investigate measures of tendency and variability, emphasizing heteroscedasticity. OLS regressions assume residuals are drawn from a population of equal variance and should not present any systematic trend. These figures investigate each independent variable at a time in each regression model. For most variables, systematic trends are visible, indicating heteroscedasticity. Newey-West standard errors are implemented in all regression models to deal with heteroscedasticity.

Figure E.1: Residual vs. Fitted values for market-to-book - HY

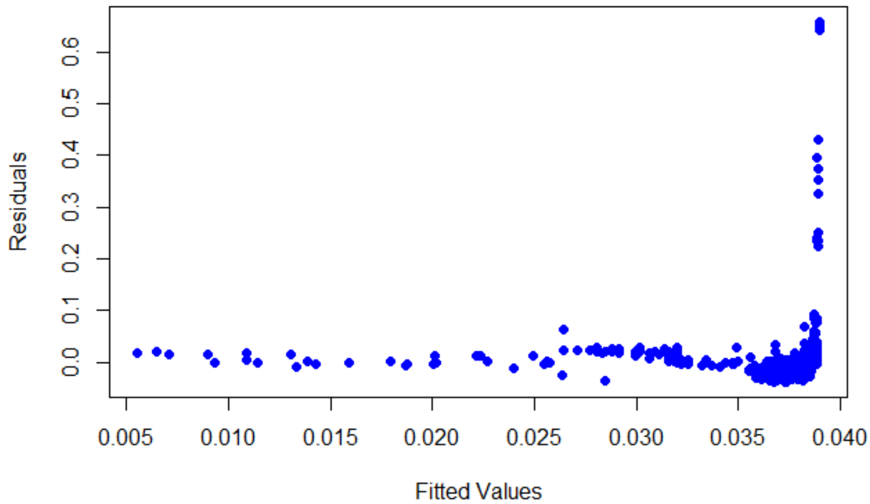


Figure E.2: Residual vs. Fitted values for market-to-book - IG

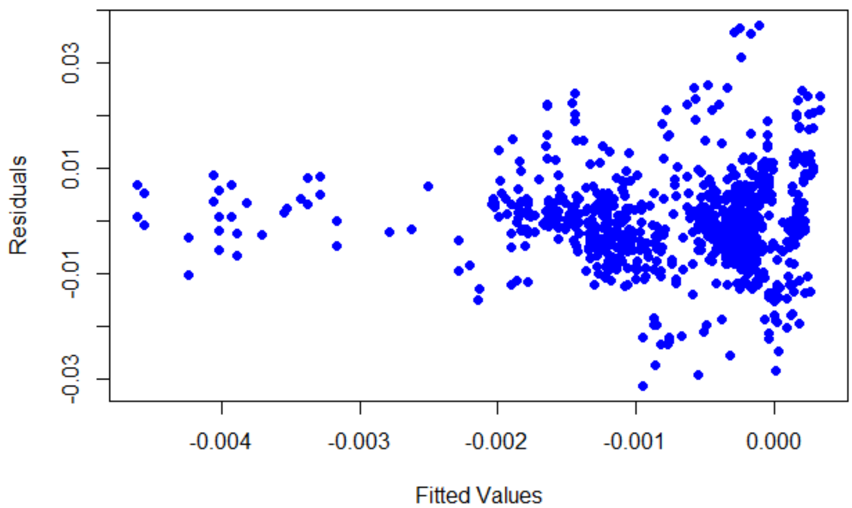


Figure E.3: Residual vs. Fitted values for covid dummy - HY

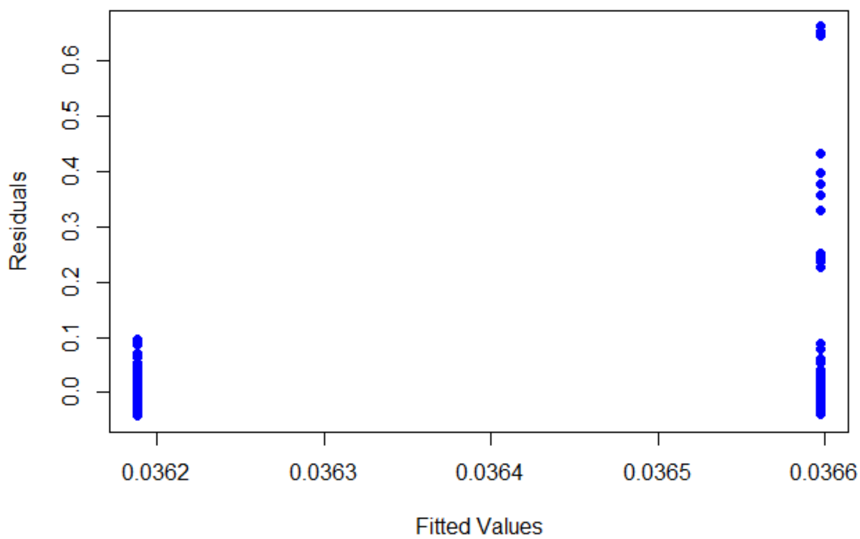


Figure E.4: Residual vs. Fitted values for covid dummy - IG

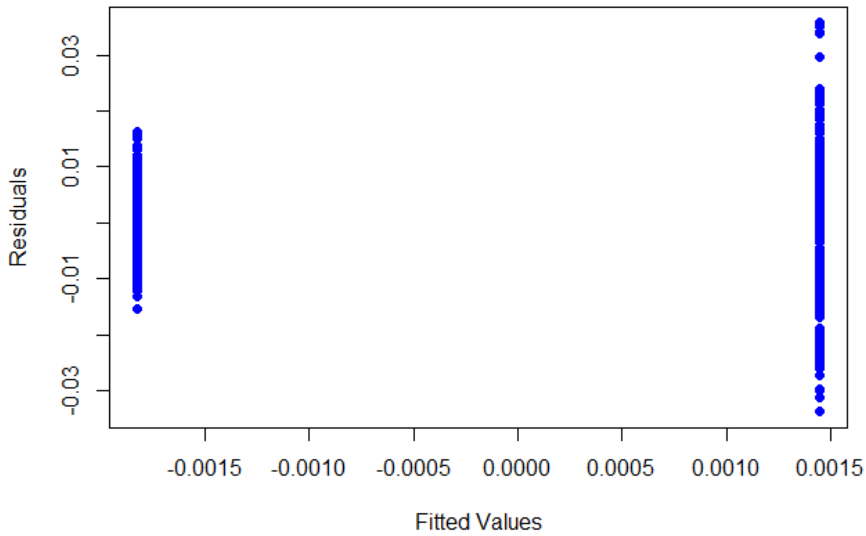


Figure E.5: Residual vs. Fitted values for OSEBX excess return - HY

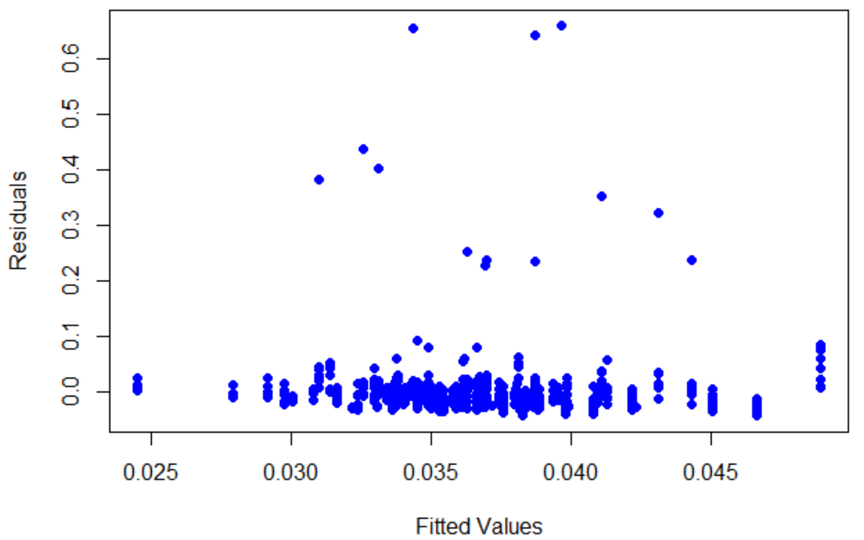


Figure E.6: Residual vs. Fitted values for OSEBX excess return - IG

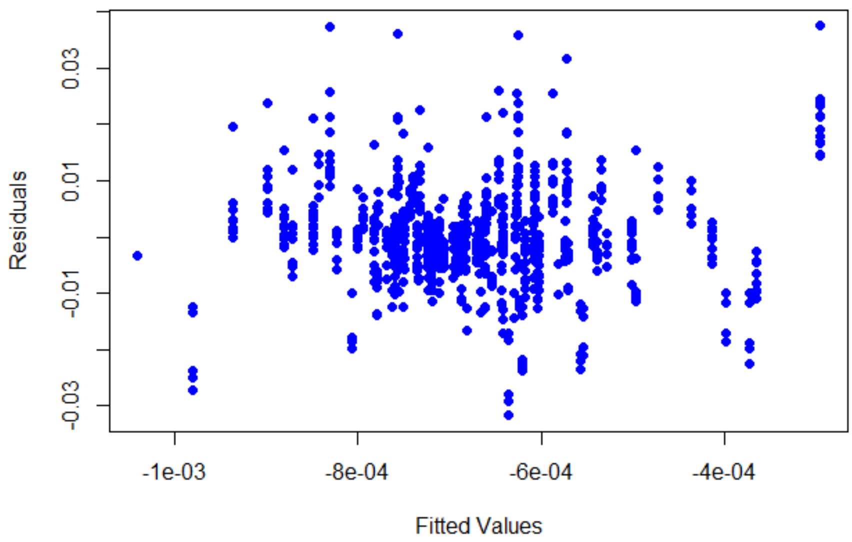


Figure E.7: Residual vs. Fitted values for OSEBX excess return - difference regression

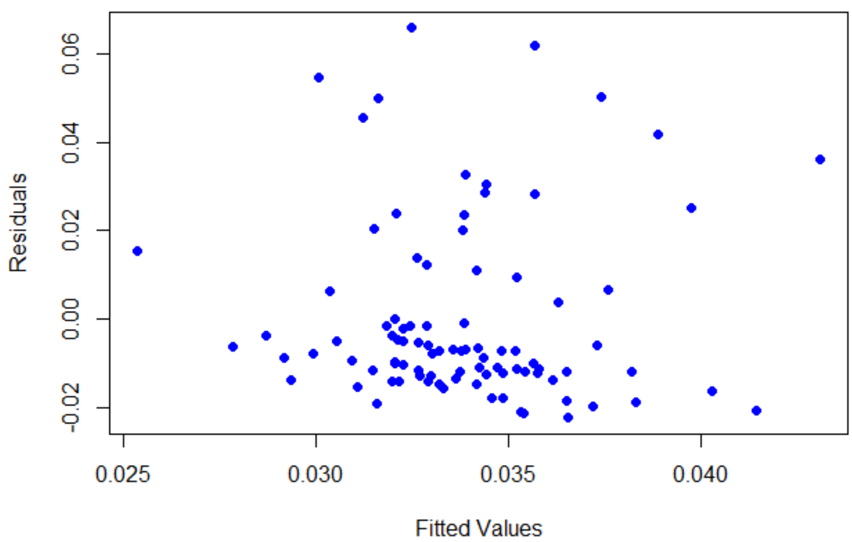


Figure E.8: Residual vs. Fitted values for oil price - HY

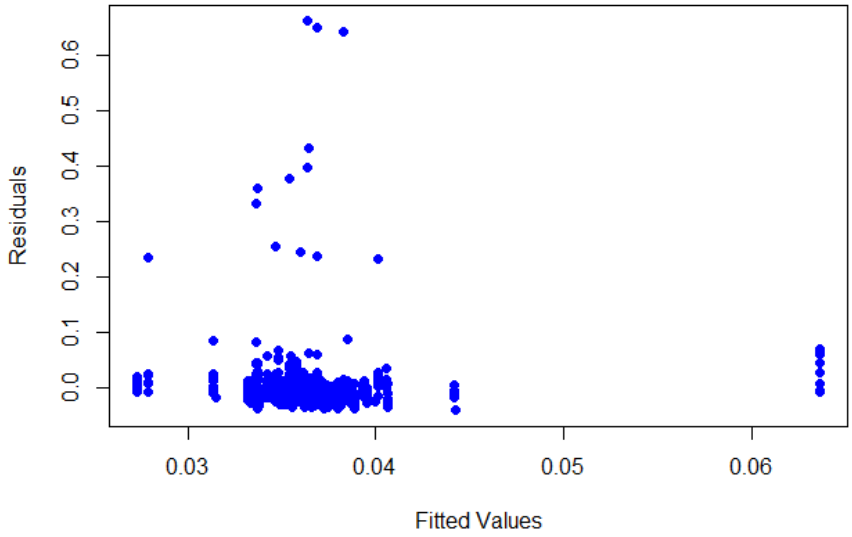


Figure E.9: Residual vs. Fitted values for oil price - IG

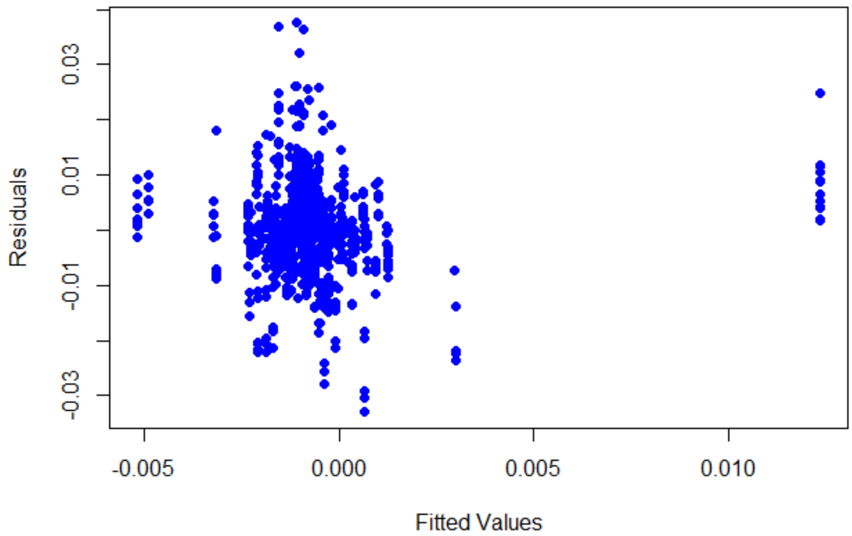


Figure E.10: Residual vs. Fitted values for oil price - difference regression

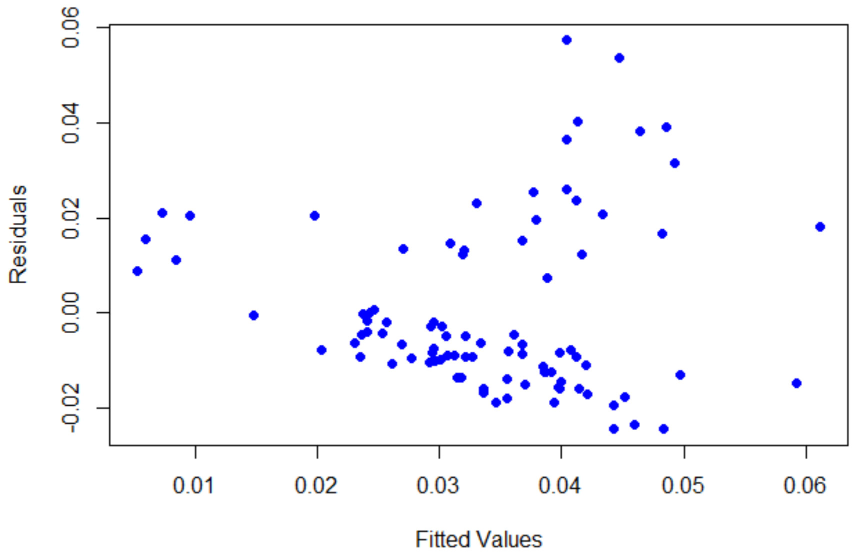


Figure E.11: Residual vs. Fitted values for Roll-Spread - HY

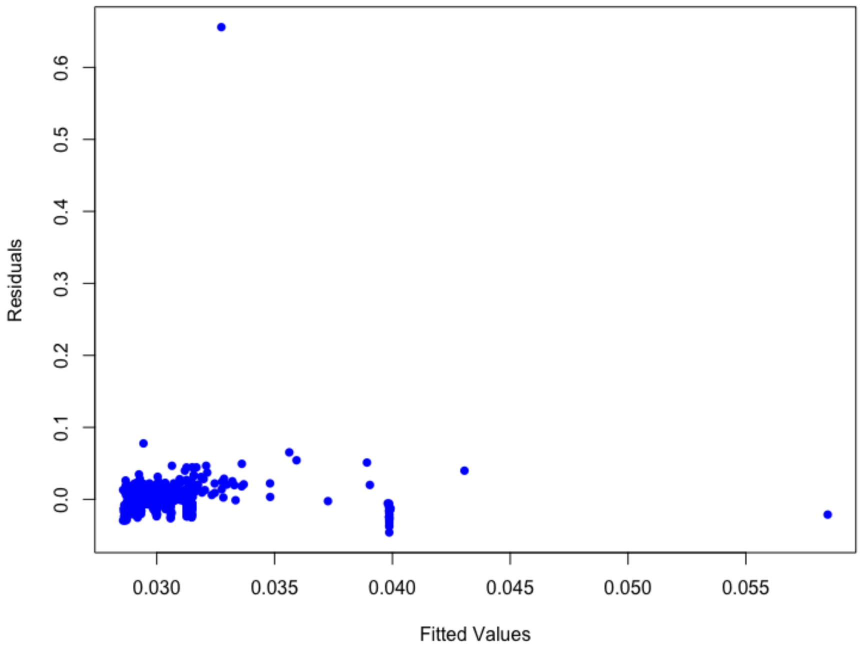


Figure E.12: Scatter plot of Roll spread vs Roll-Spread - IG

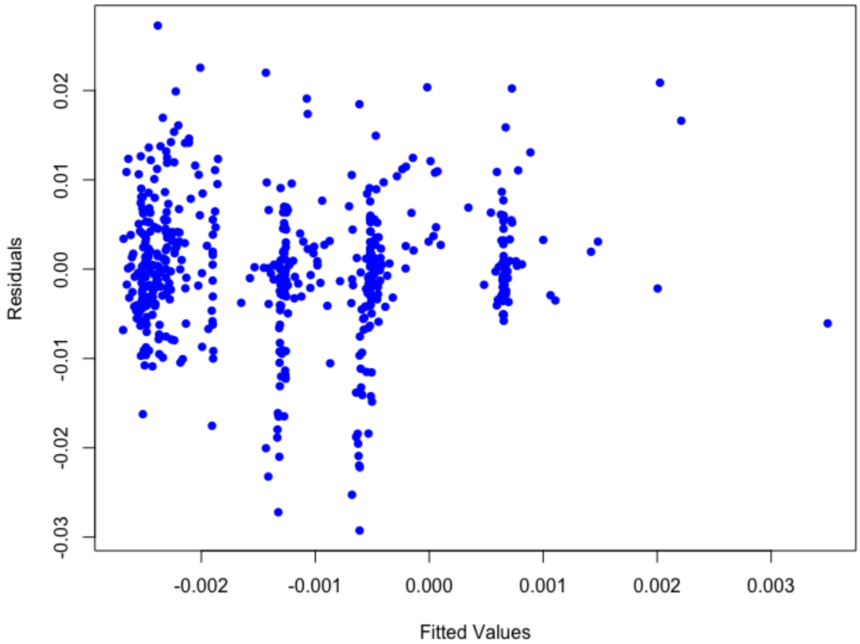


Figure E.13: Residual vs. Fitted values for TED-Spread - HY

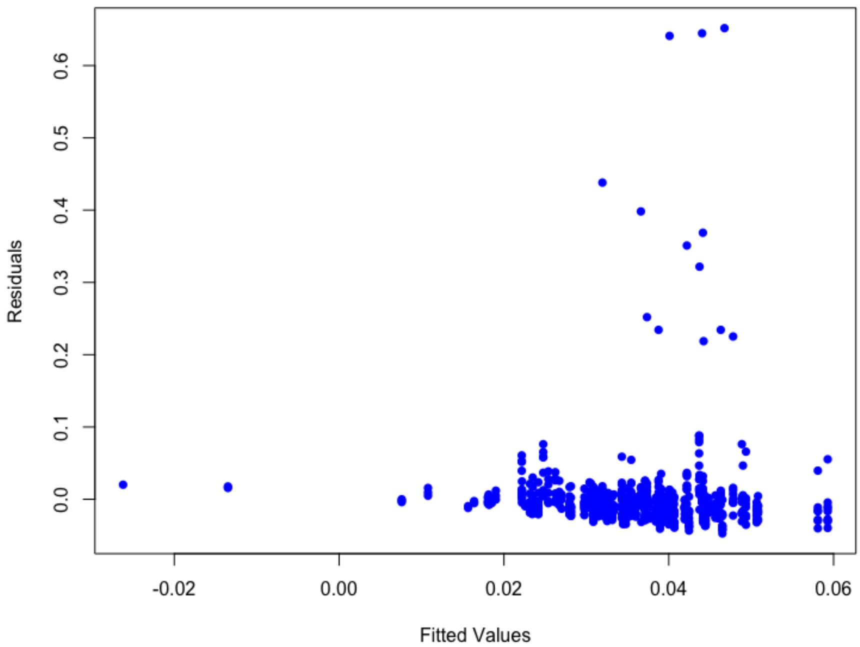


Figure E.14: Residual vs. Fitted values for TED-Spread - IG

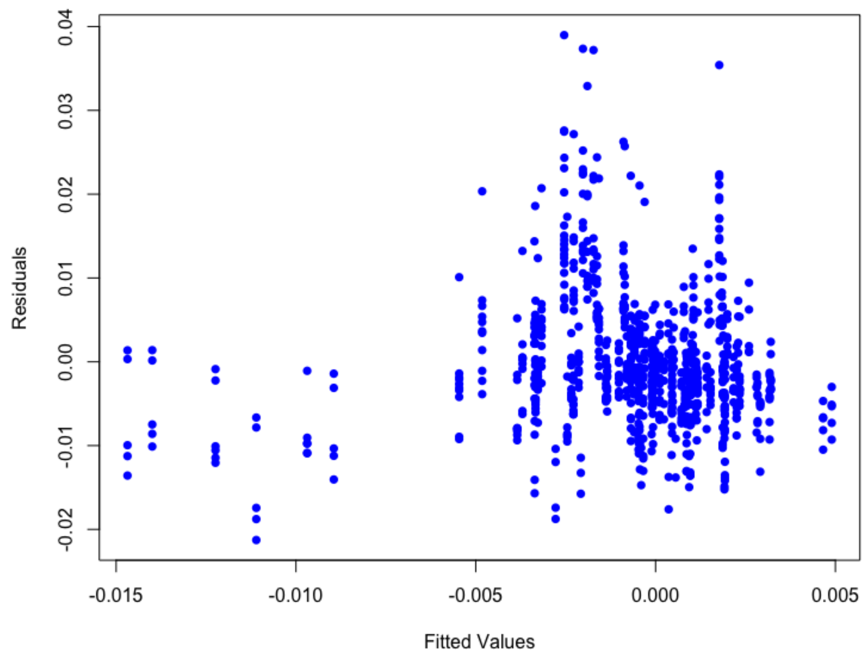


Figure E.15: Residual vs. Fitted values for TED-Spread - difference regression

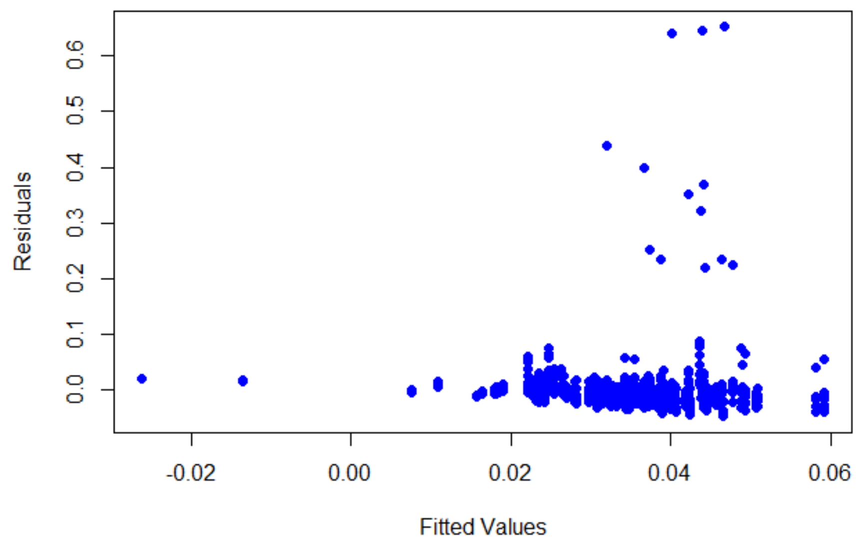


Figure E.16: Residual vs. Fitted values for coupon - difference regression

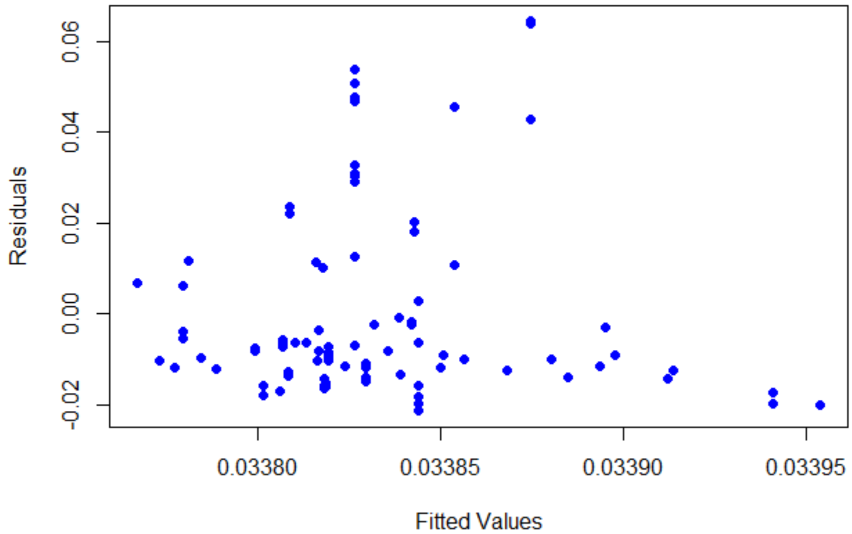


Figure E.17: Residual vs. Fitted values for maturity - difference regression

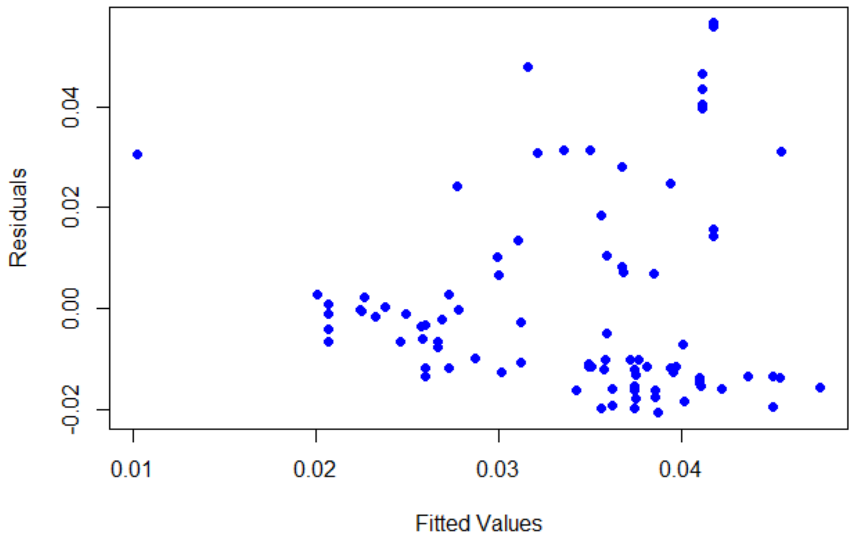


Figure E.18: Residual vs. Fitted values for leverage - difference regression

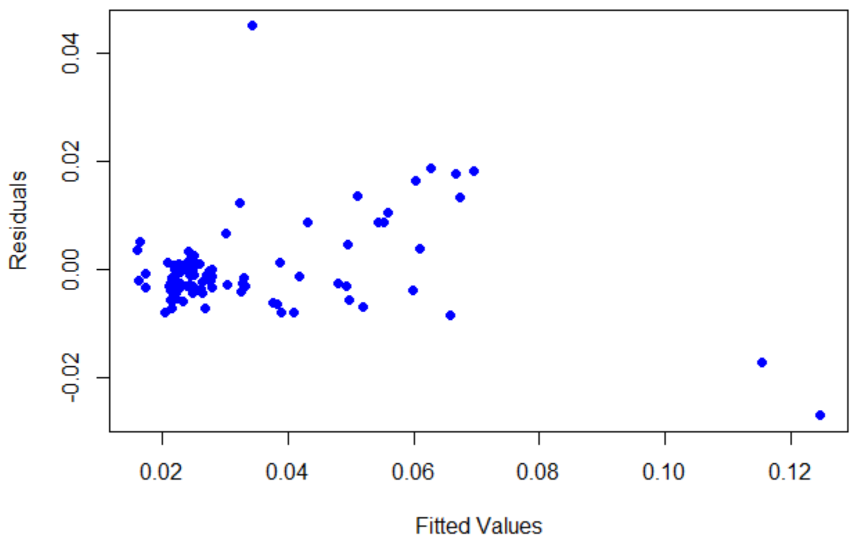


Figure E.19: Residual vs. Fitted values for asset volatility - difference regression

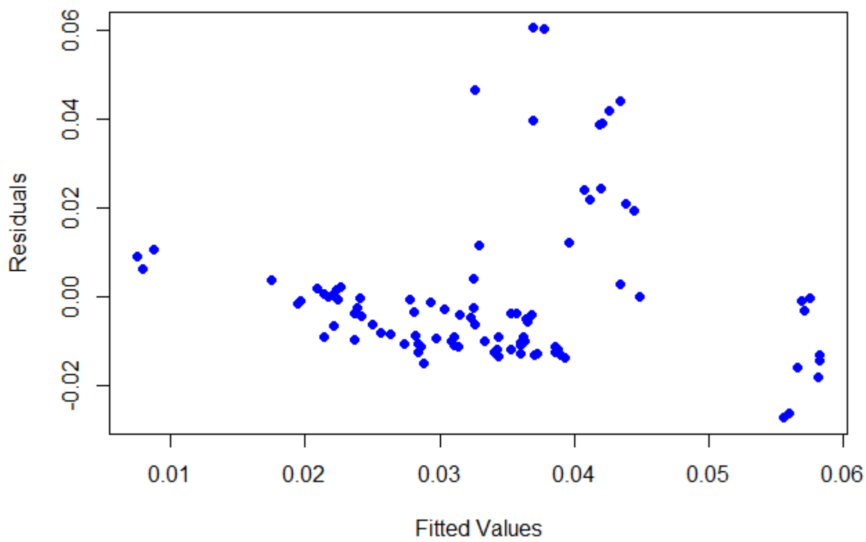
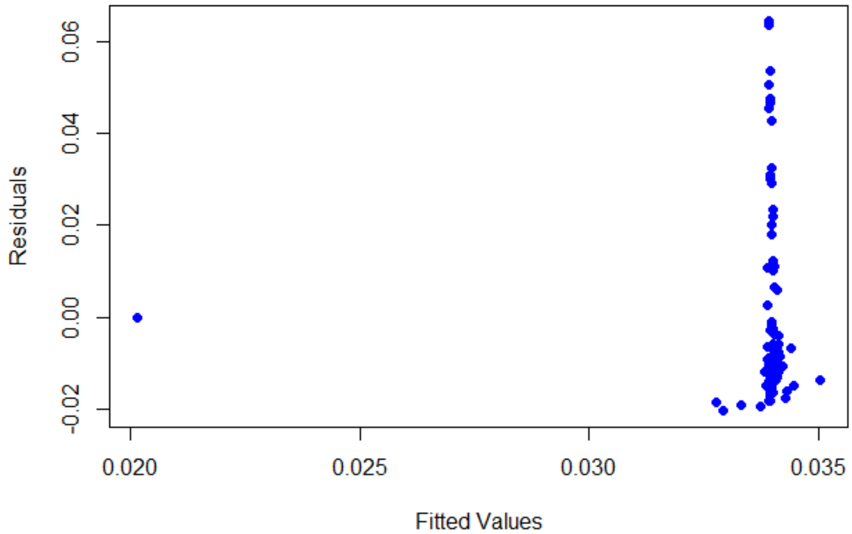


Figure E.20: Residual vs. Fitted values for credit risk - difference regression



F Roll-spread

$$2 \times \sqrt{-\text{SCov}} \tag{F.1}$$

The theoretical bid/ask spread can be estimated using F.1, where $SCov$ is the first-order serial covariance of price changes. This formula assumes that observed prices contain all relevant information. Therefore, a price change will only occur if any unanticipated information is received by the market participants, and it assumes price changes follow a random walk. There is no serial dependence in successive price changes (Harris, 1990).

G Newey-West Standard Errors

The Newey-West standard error is a statistical technique applied to cope with violations of the OLS regression assumptions, namely the presence of autocorrelation and heteroskedasticity. The formula, in short, involves choosing a number of lags to consider. We implement Newey-West standard errors using the NeweyWest function in R, choosing an appropriate lag matching our data series.