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Mind The Gap:
Decomposing the Credit Spread Puzzle

An empirical analysis of credit risk pricing in the Norwegian Corporate Bond Market in the period 2014-2023

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Abstract

This thesis presents a comprehensive analysis of the credit spread puzzle in the Norwegian corporate bond market, a topic that has been largely unexplored since 2015. Focusing on the period from 2014 to 2023, we aim to quantify the extent of the puzzle, identify additional risk premiums demanded by investors, and explore the factors driving these premiums. Our analysis of 30,647 transactions reveals that the median proportion of actual credit spreads explained by default models is 28 percent. We observe sector-specific variations, with industrial, oil, and shipping sectors showing significant mispricing. Our findings indicate that Norwegian investors seek additional compensation for sector-specific risks, particularly in the volatile industrial, oil, and shipping sectors, and for bonds from smaller issuers. A notable size premium is evident, especially in sectors susceptible to economic downturns. The study also suggests a substantial liquidity premium, challenging to quantify due to the market's illiquid nature. The research contributes to understanding the Norwegian corporate bond market's complexities, highlighting the nuanced nature of bond pricing beyond what standard models can explain.

Keywords – Credit Spread Puzzle, Merton Model, KMV Model, Corporate Bond Market

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1 Introduction

"The credit spread puzzle," where actual market credit spreads diverge from model predictions, presents a compelling challenge in financial literature. Though extensively studied globally, it remains largely unexplored in the unique context of Norwegian markets. Our research aims to clarify the credit spread puzzle in Norway, offering valuable contributions to understanding this phenomenon.

To our knowledge, the most recent examination of Norway's credit spread puzzle dates back to 2015. Acknowledging the continuously evolving market dynamics, our research revisits the topic, extending the analysis to the period from 2014 to 2023. We aim to capture the current manifestation of the puzzle in the Norwegian corporate bond market, recognizing that changes in the market could significantly alter its characteristics compared to previous findings.

We set three primary goals for our thesis, each aiming to enhance our understanding of Norway's credit market . Firstly, we aim to quantify the extent of the credit spread puzzle in the Norwegian corporate bond market, offering insights to the correlation between theoretical models and market realities. Secondly, if the credit spread puzzle exists, we seek to identify any additional risk premiums demanded by investors that may fuel this phenomenon, potentially uncovering market trends and investor sentiments. Thirdly, upon identifying these premiums, we redirect our attention to comprehending their nature and the underlying factors driving investor behavior regarding the credit spread puzzle.

Through this comprehensive approach, we emphasize our study's significance in filling a critical void in current research. We provide fresh insights and perspectives by delving into the complexities and unique characteristics of the Norwegian corporate bond market, employing methodologies similar to those used in international research.

1.1 The Credit Spread Puzzle

Bonds are a pivotal element in a company's financial strategy, serving as a crucial tool for funding their operations. Bonds represent contractual obligations where the borrower, known as the issuer, receives funds for a predefined period and agrees to ensure future repayments (Sundaresan, 2009). These repayments consist of the original amount borrowed, the principal, and an additional interest. Financial literature identifies two primary elements in a bond's interest (Sæbø, 2015). The first is the compensation for lending out money for a defined time-period. This component is represented by what is known as the risk-free rate, the return on a risk-free asset with the same time-to-maturity as the bond. However, as lending money in the fixed-income market is seldom risk-free, investors demand additional compensation for the risk that the borrower may be unable to repay its contractual obligations during the bond's term. This additional return over the risk-free asset is known as the credit spread.

Credit spreads, representing the premium investors demand to compensate for default risk, poses a significant financial enigma. Previous studies show that theoretical models, designed to forecast this risk and calculate the corresponding credit spread, frequently underpredict actual market figures. The significant divergence has sparked keen interest and debate in financial circles, leading to an intriguing phenomenon called "The Credit Spread Puzzle."

1.2 Literature Review

Introduced in 1974, the Merton (1974) model uses option-pricing theory to value risky debt, laying the groundwork for structural risk-pricing models. However, due to its practical limitations, it has been extended and refined, leading to various improved methods for precise credit risk assessment.Geske (1977) enhances the model to incorporate coupon payments as the Merton model only prices zero-coupon bonds. Jones et al. (1984) empirically tests Merton's model, finding that it has little explanatory power on real-world data. They also highlighted the potential need for stochastic interest rates[1], which Longstaff and Schwartz (1995) include in their model. Leland and Toft (1996) introduce

[1]As presented by Vasicek (1977)

endogenous bankruptcy risk and consider how credit spreads vary with debt maturity. They show that the the maturity of debt and the leverage ratio have a significant impact on the credit spread.

J.-Z. Huang and Huang (2003) estimates credit spreads using several traditional structural models and historical company data on leverage, default, and recovery rates. Their studies show that model-derived spreads are consistently lower than actual ones, and the credit risk compensation only accounts for 20-30 percent of observed spreads. This underestimation in the models they named the "credit spread puzzle."

Financial literature suggests liquidity as a critical factor causing mispricing, primarily because investors in corporate bonds often face costs when selling their investments at will. Longstaff et al. (2005) decomposes credit spreads, and finds that default accounts for 51 percent and 71 percent of credit spreads of AAA-rated and BBB-rated bonds, respectively. The unexplained component they find to be strongly related to differences liquidity differences. Houweling et al. (2005) also find that liquidity risk accounts for a significant portion of credit spreads and that this effect fluctuates over time.

Building upon the fundamental discovery that liquidity significantly influences credit spreads, further research has developed into this phenomenon. Bao et al. (2011) expands upon these initial findings by further confirming liquidity's impact on credit spreads. They demonstrate that liquidity is the most critical factor in explaining the monthly changes in the U.S. aggregate yield spreads of high-rated bonds, achieving an R-squared between 47 and 60 percent across rating categories from AAA to A. Dick-Nielsen et al. (2012) study corporate bond liquidity before and after the financial crisis in 2008-2009. Their results reveal that the liquidity premium is significantly higher for high-yield bonds than investment-grade bonds.

In his 2017 study, Ødegaard investigates bond trading on the Oslo Stock Exchange and finds that senior unsecured bonds are rarely traded. He describes the OSE as a marketplace dominated by frequent trading of only a few bonds, such as treasuries and covered bonds. At the same time, the rest are traded infrequently. Ødegaard notes the challenge in applying conventional liquidity measures for Norwegian corporate bonds, attributing these difficulties to low trading volume and lack of bid-ask spreads. Similarly, Rakkestad et al. (2013) encounter difficulties quantifying corporate bonds' liquidity for the same reason but observe that government bonds exhibit significantly higher turnover ratios than corporate bonds.

Collin-Dufresn et al. (2001) challenge the view that liquidity, default, and recovery are the driving forces between credit spreads. Their findings suggest that a constant, market-wide component is the driving force behind the credit spreads. However, Boss and Scheicher (2002) find that changes in interest rates, liquidity, and market volatility in stock and debt markets can significantly explain the observed credit spread. In addition, they agree with Collin-Dufresne et al. that there is a market-wide and unobservable component.

On the extent of broader market reaction risks, Cremers et al. (2008) explore the role of option-implied jump-risk premium in explaining the high levels of observed credit spreads. Jump-risk is the term used to describe the risk associated with sudden and significant changes in asset prices that can occur unexpectedly, causing large deviations from their average paths. Unforeseen events can cause these abrupt price shifts and significantly impact corporate bond valuation, leading to increased spreads. They use the model from J. Z. Huang and Huang (2012), incorporating jump-diffusion dynamics to investigate how jump-risks might contribute to the credit spread puzzle, typically not accounted for in other structural models. They show that including the option-implied jump-risk premium brings model spreads closer to the observed actual spreads. In this way, their findings provide insights into the significant impact of jump-risk on credit spread levels, offering a more nuanced understanding of risk compensation wanted by investors beyond default risk.

Chen (2010) studies the effect of economic business cycle variation on default risk. By including the impact of business cycles on default probabilities and losses, increased credit risk premiums help explain the credit spread puzzle.

Feldhütter and Schaefer (2014) highlight two critical shortcomings in many previous papers. First, previous papers use average firm-variables to create an average model implied spread, which they compare with an average actual spread. They argue that this leads to a convexity bias. The second bias occurs because the previous models use historical default frequencies as a proxy for expected default probabilities. Using a simulation study, they suggest using historical default frequencies for fitting future probability of default may have limited statistical power. They control for these biases and find that the evidence of a credit spread puzzle is much weaker than previous studies show. However, they acknowledge that the puzzle exists, especially for longer-term maturities.

Sæbø (2015) follows the approach of Feldhütter and Schaefer (2014) in his analysis of the credit spread puzzle in the Norwegian market between 2008 and 2013. He concludes that the credit spread puzzle is very much present in the Norwegian fixed-income market. However, he disputes to which extent it is in fact a puzzle. If an investor only gets compensated for the expected loss associated with default, it indicates that the investor is risk-neutral. As very few investors are risk-neutral and instead have some degree of risk aversion, they will demand compensation for the inherent uncertainty around the expected loss. Agrawal et al. (2004) advocates the same and adjusts the model to investors' risk aversion. Doing this, they find that default risk and risk aversion can explain 70 percent of the variation in credit spreads.

1.3 The Norwegian Corporate Bond Market

To better understand the credit spread puzzle and determine the factors that contribute to mispricing, we will begin by giving an overview of Norway's corporate bond market and some bond market basics.

In 2022, Norway's total bond market reached NOK 2,700bn, according to Nordic Trustee (2022). Presented in Figure 1.1, the market is segmented into various groups of issuers: the public sector contributed NOK 742bn, financial institutions NOK 1,300bn and the corporate bond segment NOK 628bn.

Over the past decades, the Norwegian corporate bond market has seen significant growth. Reports from Nordic Trustee indicate that from 2010 to 2022, the market's overall outstanding volume almost tripled, growing from NOK 218bn to NOK 628bn. The expansion can, amongst other factors, be attributed to higher capital requirements imposed on banks after the financial crisis, leading to increased costs for traditional bank loans (Monsen, 2020). Consequently, companies capable of accessing the bond market found more significant incentives to do so.

In the Norwegian bond market, companies have two options when issuing in the primary market: Oslo Stock Exchange (OSE) and the Nordic Alternate Bond Market (ABM). The

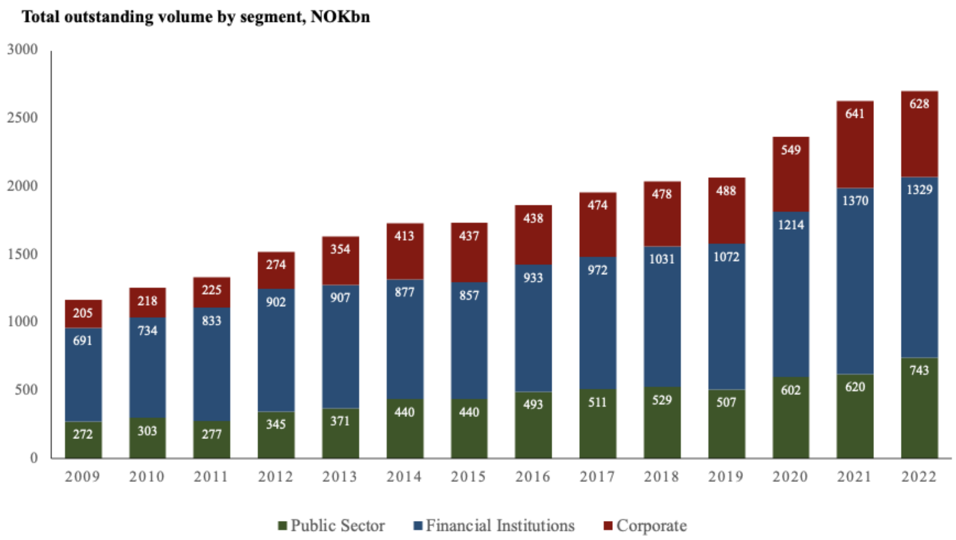

Figure 1.1: Development in the Norwegian bond market

ABM was established by OSE in 2005 and is characterized by more simplified prospectus and documentation requirements, as well as not requiring adherence to IFRS.[2] This implication is significant, and NOU (2018)[3] suggests that this can enhance smaller issuers' access to the bond market, making it a more inclusive and accessible market for a broader range of companies.

While some investors hold bonds until maturity, others may sell before expiration. These transactions occur in the secondary market, which provides liquidity and flexibility to investors who want to adjust their portfolios. In Norway, while listed bonds have the option to be traded in the secondary market through OSE's electronic trading system, the majority of corporate bond trading occurs over-the-counter (OTC), as reported by Norges Bank (2022a). In these OTC transactions, the buyer and seller directly engage with each other, frequently using brokers as intermediaries (Ødegaard, 2017). With a significant share of transactions being conducted over-the-counter, the Norwegian bond market differs from other markets.

Previously, the Norwegian bond market was predominantly occupied by power firms, as noted by Norges Bank (2023). The landscape has since shifted, and now, a substantial share of outstanding volume is by issuers in the oil, gas, and shipping sectors. As these companies are riskier, they have also given rise to a robust high-yield market in Norway.

[2]IFRS = International Financial Reporting Standards.
[3]NOU = Norges Offentlige Utredninger - Official Norwegian Reports.

High-yield bonds, as opposed to safer investment-grade bonds, are deemed to involve high risk.[4] In 2022, Nordic Trustee classified 52 percent of the NOK 628bn outstanding in the Norwegian corporate bond market as HY, amounting to NOK 327bn. This figure is significantly higher than the high-yield volume in neighboring countries, with Sweden at NOK 171bn and Denmark at a mere NOK 9bn, illustrating the prominent position of high-yield bonds in the Norwegian market.[5] Figure 1.2 presents the strong presence of high-yield bonds within the last 13 years in terms of outstanding volume.

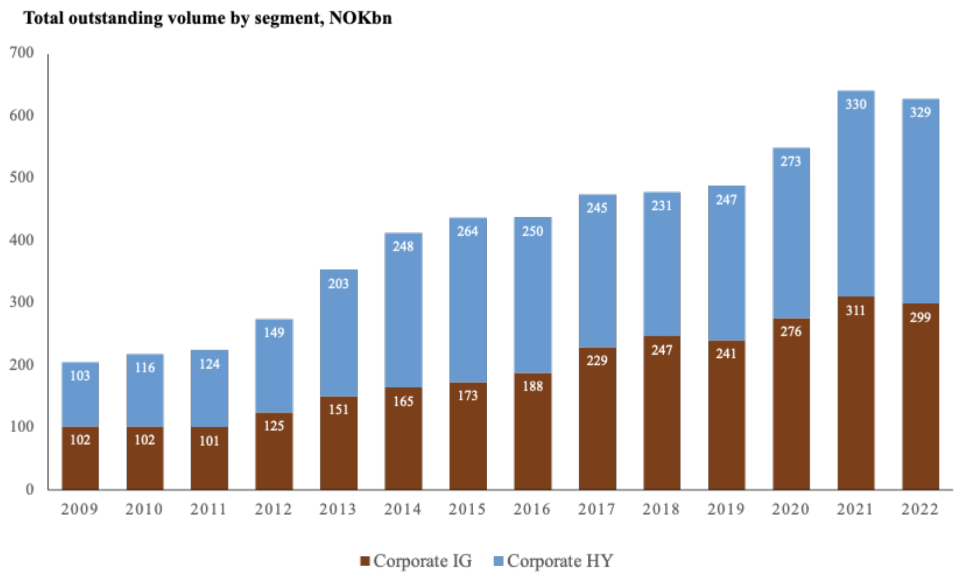

Figure 1.2: Development in the Norwegian corporate bond market

The landscape of credit ratings in the Norwegian corporate bond market also has atypical features. Unlike many other markets where most companies hold official ratings from international credit agencies, relatively few Norwegian companies, besides banks, do so, as highlighted in the NOU (2018) report. This disparity is partly attributed to Norwegian companies being relatively small in international comparison, directly affecting their credit ratings.

Until 2017, brokers and investment banks offered what was known as “shadow ratings”, akin to credit ratings and allowing for the classification of smaller issuers. With these shadow ratings, Sæbø (2015) could group issuers into ratings when analyzing the credit spread puzzle. However, EU laws on credit ratings have since banned this practice, and

[4]Due to the lack of credit ratings in the Norwegian bond market, we use Stamdata’s classification of HY and IG.

[5]Exchanged to NOK as of December 30, 2022 (Norges Bank, 2022b).

the shadow ratings are no longer available (NOU, 2018). Despite several rating agencies having entered the Norwegian market, among them Nordic Credit Rating, a significant portion of Norwegian issuers remain unrated. According to data from Nordic Trustee (2022), 58 percent of the total outstanding corporate bond volume was without a rating at the end of 2022. This trend is particularly pronounced in the HY market, with only a mere 7 percent of the volume rated.

In conclusion, the Norwegian corporate bond market exhibits unique characteristics and has undergone a substantial evolution, particularly in the growth of the high-yield segment. These factors, combined with the shift in the market's composition and the predominance of unrated issuances, present distinct challenges and opportunities in understanding and navigating this market.

2 Methodology

To comprehend the concept of credit spreads, we shall implement a structural model based on the Merton (1974) model. Firstly, we will elaborate on the theoretical aspects of the Merton model. Subsequently, we will delve into the practical implementation of the Merton Model through the KMV Model, the primary model used in our thesis. By doing so, we aim to understand the credit spread puzzle comprehensively.

2.1 The theoretical aspects of the Merton model

The Merton (1974) Model, introduced by Robert C. Merton, builds upon the Black and Scholes (1973) option pricing model to value a firm's equity and debt. It suggests that equity can be seen as a call option on the firm's assets, granting shareholders the right, but not the obligation, to "buy" the firm's assets by paying off the debt. Conversely, debt can be analogized to being short a put option, reflecting the right shareholders have to "sell" the firm's assets to creditors in the event of default.

Owning debt in a firm can be likened to a combination of a risk-free loan and a put (Sundaresan, 2009). The risk-free loan symbolizes the face value of the debt, which is the best return the creditors can receive, even if the company performs well. If the firm underperforms, the most they can hope to recover is the value of the assets at the time of default. In this case, shareholders can transfer the firm's assets to the creditors due to their limited liability and walk away from any further debt responsibilities. This scenario is akin to exercising a put option on the firm's assets, with a strike price equal to the face value of debt. Therefore, the value of debt can be seen as the value of the risk-free loan minus the value of the put option the shareholders possess.

Therefore, the value of debt at time T can be defined as:

$$D_T = \min(F, V_T) = F - \max(V_T - F, 0) \tag{2.1}$$

V_T represents the uncertain future value of the firm's assets at time T and F the face value of debt. If the value of a company's asset exceeds the debt at maturity ($V_T > F$), the creditors are repaid in full. However, if the assets are worth less than the face value

($V_T < F$), the equity owners hand the firm's assets over to the creditors, who receive the asset's value as repayment instead of the original debt amount.

Merton (1974) treats the value of a firm's equity as a call option on the firm's assets, with the debt's face value F as the strike price. When the firm's value surpasses the face value, the equity owners repay the creditors and keep whatever is left. The call option is worthless if the firm value is lower than the asset value.

$$E_T = \max(V_T - F, 0) \tag{2.2}$$

Using these relationships, Merton (1974) valued corporate debt using option pricing theory, focusing on the likelihood that the firm's asset will be worth less than the face value of debt at maturity. The model employs some key inputs that influence this probability:

1. **Leverage:** Higher leverage means that the debt's face value will be closer to the total firm value, increasing the probability of the firm value dropping below face value.
2. **Volatility of Firm Value:** Significant volatility in the firm's value increases the possibility of a considerable decrease, which increases the probability of default.
3. **Time to Maturity:** Longer maturities expand the space of potential outcomes, increasing the risk associated with the debt.

Merton used these input factors, combined with the risk-free rate, to assess the value of corporate debt and estimate the default spread. Despite its inherent simplifications and strong assumptions, the Merton model has been a fundamental framework for calculating and understanding default spreads.

2.2 The practical implementation: The KMV Model

Our thesis employs Moody's KMV Model to calculate default probabilities, a model analogous to the Merton (1974) Model. Using the CreditEdge™ of Moody's Analytics, we analyze prospective default probabilities. This subsequent section will detail the KMV approach fundamental to Moody's CreditEdge™.

Contrary to Merton, the KMV Model introduces a more nuanced perspective on credit risk (Crosbie & Bohn, 2003). It posits that default is triggered not merely due to a firm's assets devaluing to a certain threshold but also due to the firm's liquidity constraints and cash flow adequacy. The KMV Model acknowledges that asset value, while a critical indicator, is not the sole determinant of default probability. A firm can often continue operations and stave off default through solid cash flows, even though the liabilities outstrip the asset base.

The KMV Model has three steps in calculating a firm's default probability: estimating the asset value and asset volatility, calculating the distance-to-default, and calculating the default probability.

Estimating asset value and volatility begins with using market equity prices, as per Crosbie and Bohn (2003), employing an option-based approach. The asset's market value is deduced from equity market values and financial statement data (Sundaresan, 2009). For asset volatility, five years of monthly observations of the market value data is used (Sæbø, 2015). In instances with limited historical data, estimates of asset volatility and value are derived using comparable companies.

The Default Point (DP) represents the threshold at which the market value of the assets must fall below for default to occur (Crosbie & Bohn, 2003). The DP is calculated from the firm's financial obligations. For non-financial companies, the DP is calculated based on the sum of all short-term and half the long-term debt. The threshold for financial companies is 75 percent of total liabilities, reflecting the unique aspects of their capital structure and asset liquidity. The Default Point concept resembles the face value of debt in the Merton (1974) Model, which also denotes the critical level assets that must fall below to trigger a default.

A key metric, the Distance-to-Default (DD), quantifies the divergence between the market value of the firm's assets and the Default Point (Crosbie & Bohn, 2003). This distance is estimated using six input variables:

1. The current asset value
2. The distribution of the asset value at time H
3. The volatility of the future asset value at H

4. The default point, DP

5. The expected rate of growth in the asset value over the horizon.

6. The length of the horizon.

Using these six input variables, the KMV model can quantify the distance from the firm from default, measured in standard deviation units. The conceptual framework is outlined in Figure 2.1.

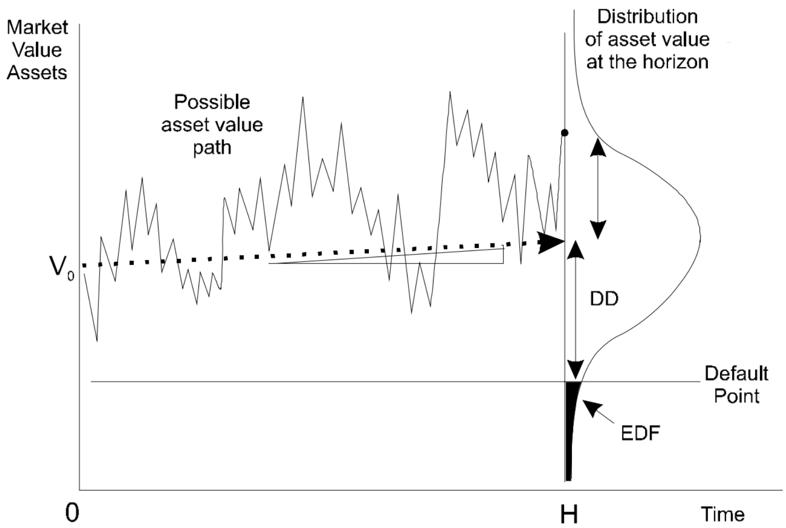

Figure 2.1: Default probability of a firm over some horizon using the KMV Model (Crosbie & Bohn, 2003).

After computing the Distance-to-Default, the estimated default frequencies, EDFs, can be determined (Crosbie & Bohn, 2003). The process involves establishing a correlation between DD and default probabilities based on historical data on default and bankruptcy frequencies. The default probability is estimated by aligning the DD with a historical default distribution for the same time frame. For instance, consider predicting the default probability over the next two years for a firm with a distance to default of five. To do this, we reference the historical default frequency of companies with comparable DD and that defaulted within a two-year time frame. This method actively estimates the probability of default.

The reliance on historical defaults for predicting future ones, a key feature in the KMV Model, has faced criticism. As discussed, Feldhütter and Schaefer (2014) argue that this approach has limited effectiveness when forecasting future default rates, as demonstrated by their simulation study. This viewpoint challenges the assumption that past default rates are reliable indicators of future risk. However, Moody's Analytics has proven robust predictive capabilities in their model. Malone and Choi (2019) illustrate this, showcasing that it has accurately and timely predicted high-yield default rates. Crossen and Zhang (2011) come to the same conclusion when validating the EDF model on European corporate firms. These studies underscore the model's competency in accurately forecasting default probabilities despite Feldhütter and Schafer's criticism of one of its fundamental assumptions.

2.3 Estimation of model spreads

A risk-neutral investor can expect compensation for the expected loss associated with his investment. The expected loss depends on the likelihood that the issuer defaults and the anticipated loss magnitude should such a default occur. To quantify this, we employ a concept known as the "model spread," the correct spread given the probability of default and loss given default. Our methodology is anchored in the work of Sæbø (2015), which adapts the foundational formula of Agrawal et al. (2004).

$$\text{Model Spread}_{it} = -\frac{1}{T}_{i,j} \ln\left(1 - CPD_T \times LGD\right) \tag{2.3}$$

In this context, T represents the time-to-maturity of the bond as of the transaction date, measuring the remaining lifespan of the bond. CPD, the cumulative probability of default, denotes the aggregate probability that the issuing firm will default within a time frame mirroring the bond's time-to-maturity. The loss given default, LGD, represents the potential loss in the event of a borrower's default. The LGD is the expected financial loss when the borrower fails to fulfill their debt obligations. Thus, applying these variables, Equation 2.3 calculates the credit spread for each bond transaction, offering a precise estimate of the risk premium demanded by investors to compensate for the risk of default.

Probability of Default

Our analysis uses Moody's CreditEdge™ to assess cumulative probabilities of default, as outlined in section 2.2. This model provides prognostic estimates of Expected Default

Frequencies (EDFs) by implementing the KMV approach.

Moody's CreditEdge™ platform is extensively tested and proved to be a market-leading estimator of true default probabilities (Crossen & Zhang, 2011). Therefore, as we want estimates as precise as possible to fulfill our main goal of quantifying the extent of the credit spread puzzle in the Norwegian market, we use the values from Moody's CreditEdge™ as our cumulative probabilities of default.

Loss given default

Loss given default, LGD, represents the financial loss the investor suffers on his investment when the issuer defaults. Default typically occurs when a firm files for bankruptcy, at which creditors are entitled to claim the firm's assets, as outlined by Sundaresan (2009). The LGD value differs between firms, predominantly influenced by the value of the firm's assets at the time of default. Additionally, for a single issuer, LGD can differ depending on the bond's position within the capital structure.

Secured bonds, backed by specific assets pledged as collateral, provide investors with a direct claim in the event of default, as Berk and DeMarzo (2023) note. This collateral agreement makes them safer than unsecured bonds, where investors can claim any remaining assets not already pledged as collateral by the senior bondholders. However, determining the LGD for senior bonds requires valuing each bond's collateral. Therefore, we only include senior unsecured bonds to make our sample as homogeneous as possible.

With limited Norwegian research on loss given default, we rely on European data from Altman and Kuehne (2012), who measure recovery rates. A recovery rate is essentially the opposite of loss given default and denotes the portion of the original investment the investor can expect to recover in the case of default. Altman and Kuehne estimate recovery rates by observing traded prices immediately after the case of default between 1971 and 2011. Their study stands out for categorizing these rates by both sector and bond seniority, providing more relevant and targeted recovery rates to our study.

The recovery rates are estimated by observing traded prices immediately after the case of default. Where Altman and Kuehne's study differs from other on the same topic, is that they group their estimates into both sectors and bond seniority. Therefore, for senior unsecured bonds, they have recovery rates for 11 different sectors.

In our study, we adopt an approach similar to Sæbø (2015), who used a heterogeneous recovery rate across various sectors, contrasting Feldhütter and Schaefer (2014) method of a static recovery rate. We employ the recovery rate estimates from Altman and Kuehne, acknowledging the significance of varying recovery rates in different industries. Our sample includes a broad range of sectors, and we follow the methodology of Sæbø, using the recovery rate estimates from Altman and Kuehne (2012). This heterogeneity in recovery rates allows us to differ between companies with substantial fixed assets, such as utility companies and industrial firms, and those with less collateral, as the more typical miscellaneous firm.

In the analysis, we have grouped the sample into four broad sectors and assigned specific recovery rates to each, based on Altman and Kuehne (2012) findings. We set the recovery rates for the financial and utilities sectors to 49.2 and 70 percent, respectively. In the "Industrial, Oil and Shipping" category, the recovery rate of 48 percent is the average of Altman and Kuehne's energy and miscellaneous sectors. The final category, our miscellaneous sector, includes diverse seafood, media and transportation industries. Here, we set the recovery rate to 38.7 percent, the average of Altman and Kuehne's conglomerates, health care, leisure, media, retail and transport sectors.

Table 2.1: Sectors and their corresponding industries along with recovery rates and LGD

Sector	**Industry Group**	**Recovery Rate**	**LGD**
Financial	Bank Insurance	49.2%	50.8%
Industrial, Oil and Shipping	Industry Oil and Gas E&P Oil and Gas Services Shipping	48.0%	52.0%
Utilities	Utilities	70.0%	30.0%
Miscellaneous	Convenience goods Media Pulp, Paper and Forestry Real Estate Seafood Telecom/IT Transportation	38.7%	61.3%

Using these sector-specific recovery rates, we can for every transaction calculate the loss given default by the following formula:

$$\text{Loss Given Default} = 1 - \text{Recovery Rate} \tag{2.4}$$

Having the cumulative probability of default and the loss given default, we can compute the default-derived model spread for every transaction. To determine the mispricing, we then need to estimate the actual spreads.

2.4 Estimation of actual spreads

Calculating the spread for each transaction requires subtracting the risk-free rate from the yield-to-maturity, as shown in Equation 2.5.

$$\text{Spread}_{i,t,T} = \text{Yield-to-Maturity}_{i,t} - \text{Risk-free yield}_{t,T} \tag{2.5}$$

The credit spread for a bond i at time t, maturting at time T is calculated by the difference between the bond's yield-to-maturity at time t and the risk-free yield with the same maturity.

Therefore, to accurately estimate the credit spread for each transaction, we must first calculate the yield-to-maturity before subtracting the appropriate risk-free rate. Due to certain aspects of the risk-free rate being crucial in the estimation of yields, we begin by outlining our methodology for determining risk-free rates.

2.4.1 Determining the appropriate risk-free rate

Internationally, economic literature often uses government securities as proxies for risk-free assets. However, alternative measures might be more suitable in Norway due to specific market characteristics in the Norwegian markets. Rakkestad and Hein (2004) argue that the small size of the Norwegian government bond market leads to poor liquidity and low outstanding volume. Therefore, government bonds are considerably influenced by variations in supply and demand and do not truly reflect changes in the risk-free required rate of return. This diminishes their reliability as a benchmark for long-term rates and corporate bonds. Based on these considerations, Rakkestad and Hein suggest swap rates, as they tend to offer more stable yields and better represent the risk-free rate in the Norwegian context.

Interest swaps are agreements where two parties exchange periodic payments based on a principal amount. In such arrangements, described by Sundaresan (2009), one party pays floating rates while the other pays a fixed rate. A 3-year swap rate, for instance, is the fixed rate a party can agree to pay instead of a floating interest rate for three years. These swap rates are an essential part of the financial system and are observable in sources for financial data.

Swap rates, while helpful, have the limitation that they are unavailable for maturities under one year. For these shorter durations, interbank rates are the only adequate alternative to the government rates. Interbank rates are essentially the rates at which banks offer loans to other banks (Sundaresan, 2009). In Norway, the interbank rate is referred to as the Norwegian Interbank Offering Rate, NIBOR, and is available for maturities from 1 week to 6 months.

However, the disadvantage of using interbank rates for short-term yields is that these rates are affected by liquidity and credit conditions in the interbank market. Therefore, in scenarios where the banking sector experiences significant economic shocks, the interbank rates can deviate from the true risk-free asset. Bernhardsen et al. (2012) provide empirical evidence of this dynamic. They observed that during and in the aftermath of the financial crisis of 2008-2009, there was a significant risk premium in the NIBOR rates, making them converge from the true risk-free asset. Such periods of financial turbulence highlight the limitations of using the interbank rates as proxies for risk-free rates.

However, according to Hull et al. (2004), the market uses a risk-free rate of about ten basis points less than the swap rate. This proxy for the risk-less asset is also used by Sæbø (2015), and is the same one we adopt for in our estimation of risk-free rates. The reason for subtracting ten basis points from the swap rate is that the swap rate includes some counter-party risk. The swap rate is also used as proxy for the risk-free rate in newer literature on the credit spread puzzle, as in Bai et al. (2020), strengthening our arguments for choosing this proxy.

We gather data for NIBOR and NOK swap rates for every trading date from 2014-2023. NIBOR rates are available for maturities of 1 week and 1, 2, 3, and 6 months, while swap rates are quoted in the market for durations ranging from 1 to 10 years. We can construct a complete yield curve for every trading date with this data by employing interpolation techniques. The interpolated yield curve is essential in our analysis as it determines the risk-free rates. By applying this curve, we can accurately pinpoint the risk-free rate for each transaction based on its time-to-maturity and trade date.

2.4.2 Determining the yield

The yield-to-maturity of a bond is defined by Caks (1977) as the discount rate such that

$$P = \sum_{n=1}^{N} \frac{C}{(1+y)^n} + \frac{F}{(1+y)^N} \tag{2.6}$$

where P is the price of a bond with N periods left to maturity, C is the coupon to be paid at the end of each of the next N periods, F is the face amount to be paid at maturity, and y is the yield-to-maturity.

It is important to note that this formula gives the dirty price of the bond, a concept explained by Choudhry (2010). As it is the bond owner on the dividend date who receives the whole coupon payment, buying a bond between dividend dates will also buy the right to the interest payments accrued from the last dividend until the next. The bond price including accrued interest is called the dirty price. The clean price is the bond price, assuming that the buyer will only receive part of the following coupon payment that has occurred under his ownership. The clean price is usually the price that is quoted in financial markets, while the dirty price is what the buyer pays. The clean price is also the price Euronext Oslo Stock Exchange quotes, where we received trade prices (Euronext, 2021). However, for the yield calculations to be correct, it is essential that we incorporate the accrued interest and thereby revert to the dirty price. This adjustment ensures that our yield calculations reflect the total cost an investor incurs when purchasing a bond.

$$\text{Clean Price} = \text{Dirty Price} - \text{Accrued Interest} \tag{2.7}$$

Our sample consist of both fixed-rate and floating-rate coupon bonds, who require different approaches in the calculation of the yield-to-maturity.

Fixed-rate Bonds

The calculation of yields for fixed-rate bonds uses Equation 2.6. It requires six key factors: Settlement date, maturity date, coupon rate, clean price, redemption type and the frequency of coupon payments. The settlement date is the day the security is transferred, which, according to Finance Society Norway (2020), is by convention two trading days after the trade date. The maturity date, coupon rate, redemption type and frequency of coupon payments are detailed in the bonds's contract and can be sourced from Stamdata's database.

Our analysis focuses exclusively on bullet bonds, where the whole principal amount is paid at maturity. Additionally, most fixed-rate bonds in our sample have an annual frequency, meaning coupon payments are made once a year.

Floating-rate Bonds

The yield calculation of fixed-rate bonds is generally straightforward, but it becomes considerably more complex for floating-rate bonds. The floating coupon rate comprises a benchmark rate, subject to periodic resetting, and a fixed credit margin. In our case, almost all floating rate bonds have the 3-month Norwegian Interbank Offering Rate, NIBOR, as the benchmark for the floating component. The 3-month NIBOR determines the coupon rate for these bonds as of the last reset date, plus the fixed element, which stays constant for each bond. These bonds reflect market conditions more dynamically than fixed-rate bonds, which requires a more nuanced approach to the yield calculation to account for the fluctuating nature of the coupon rate.

As the future NIBOR rates are unknown, so is the exact yield to maturity of floating rate bonds. However, the yield can be estimated using the market participants' best estimates of future NIBOR rates. Using these, the yield can be estimated, as in Equation 2.8.

$$P = \sum_{n=1}^{N} \frac{(NIBOR^n + m)}{(1+y)^n} + \frac{F}{(1+y)^N} \tag{2.8}$$

As for the fixed-rate bond, P is the price of a bond with maturity N, F is the face amount to be paid at maturity N, and y is the yield to maturity. $NIBOR^n$ is the floating element of the coupon payment in period n, while m is the fixed margin, which stays constant for each bond.

First, we locate each bond's installment dates, which is the date when coupon payments are received. The bond's floating rate is determined on the interest fixing date, conventionally two trading days before the installment date, and it sets the rate for the upcoming period (Finance Society Norway, 2020). To illustrate, if a bond has installment dates on the 15th of February and the 15th of May, the floating rate for the 15th of May coupon payment will be set on the 13th of February.[6]

Consequently, the floating element is predetermined on the trade date for all floating-rate observations. We set the NIBOR rate for the upcoming coupon payment to the 3-month NIBOR rate on the last interest fixing date before the trade date. We apply the "modified following business day" approach to find the exact fixing date, aligning with the convention in Norwegian bond markets (Finance Society Norway, 2020). If the fixing date is not on a trading day, the installment date shifts to the upcoming one. However, if the relocation results in a change into a new calendar month, the fixing date is moved to the last trading day prior to the original installment date.

After gathering the NIBOR rate for the first installment, we need to estimate the future NIBOR rates. For each transaction, we identify each of the remaining interest fixing dates. Then, using the yield curve for each transaction, we can estimate expected NIBOR rates based on forward rates. Forward rates are used under the assumption that these rates reflect information on market expectations of future spot rates. The methodology is grounded in the law of one price, suggesting that the expected return on a risk-free asset over a certain period should be equivalent to two consecutive shorter risk-free investments over the same period. Using this, we can find the expected NIBOR rate between year 1 and 2 by using the 1 and 2-year yields, as in Equation 2.9.

$$(1 + y_2)^2 = (1 + y_1) \cdot (1 + f_{1,2}) \tag{2.9}$$

In that way, the forward rate, expressed annually, between time k and j, where j > k can calculated by solving the following equation:

$$f_{j,k} = \left(\frac{(1 + y_j)^j}{(1 + y_k)^k} \right)^{\frac{1}{j-k}} - 1 \tag{2.10}$$

[6]Assuming that all of these are actual trading days.

Leveraging this formula, we can, for each transaction, accurately estimate future NIBOR rates for all installment dates.

With all forward rates for each transaction estimated, we can project future coupon payments by adding the expected NIBOR rate to the fixed margin. Since both the coupon margin and the NIBOR rates are expressed as annual rates, the coupon payment requires adjustment according to the frequency of coupon payments. For example, for a bond with quarterly installments, each coupon payment is calculated by dividing the sum of the two annual by four. The yield can now be calculated by solving the following formula:

$$P = \sum_{n=1}^{N} \left(\frac{\frac{(NIBOR^n + m)}{4}}{(1+y)^t} \right) + \frac{F}{(1+y)^T} \tag{2.11}$$

Applying this formula, we then have the yield-to-maturity for all floating rate transactions.

2.5 Calculation of Actual Spread

After calculating the yields for both fixed and floating bonds, we can determine the spreads. The spread is the difference between the yield of the bond and the risk-free yield for the same maturity as the bond.

$$\text{Actual Spread} = \text{Yield-to-maturity} - \text{Risk-free yield} \tag{2.12}$$

Following the approach described in this section, we can estimate the actual spread for all transactions in our sample.

2.6 Mispricing Measures

With both the actual traded spreads and the default-derived model spreads estimated, we can calculate the mispricing for every transaction.

The mispricing between the actual and model spreads can be expressed in absolute or relative terms. We define the explained share as the share of the actual spread observed caused by the model spread, expressed as a percentage. A percentage over 100 would indicate that the spread implied by the model is higher than the actual spread.

$$\text{Explained Share} = \frac{\text{Model Spread}}{\text{Actual Spread}} \tag{2.13}$$

Furthermore, we define absolute mispricing as the mispricing between the actual and model spread, expressed in absolute terms. Here, we subtract the model spread from the actual spread and measure in basis points. A positive number would indicate that the actual spread is higher than the model spread. Due to a skewness in the distribution of actual and model spreads our main approach is to use median values.

$$\text{Absolute Mispricing} = \text{Actual Spread} - \text{Model Spread} \tag{2.14}$$

Using the approach of measuring the mispricing on every transaction, and not on cross-sectional averages, we correct for the bias described by Feldhütter and Schaefer (2014), allowing us the measure the extent of the credit spread puzzle as accurately as possible.

2.7 Overview of Empirical Method and Variables

This section outlines the empirical approach to analyzing credit spread discrepancies' determinants. We begin by selecting variables based on their relevance to sector risk, leverage, market volatility, and liquidity, as identified in the existing literature. Following the variable selection, we describe the regression model used to investigate the relationship between these factors and the absolute mispricing in credit spreads.

2.7.1 Variable Selection

Sector variables

Studies have shown that sector risk may contribute to the credit spread puzzle. Sæbø (2011) finds that nearly half of the credit spread variation beyond default risk is due to risk averse investors shying away from particular sectors. To address this, we have incorporated sector dummies, anticipating varying impacts on the puzzle and serving as control variables for sector-specific effects on the other independent variables.

Firm-specific variables

We include the leverage ratio in our model to account for its potential impact on credit spreads, as suggested by Collin-Dufresn et al. (2001), who argue that within a structural framework, a company's default risk increases as its leverage ratio approaches unity, leading to wider credit spreads. Studying the credit spread puzzle, Eom et al. (2004) find that models often overpredict spreads for bonds with higher leverage ratios and underpredict those with lower. Numerous newer studies agree, and Bai et al. (2020) argue that there is a credit spread puzzle in investment grade bonds, but not in higher-levered high-yield bonds. Feldhütter and Schaefer (2018) strongly disagree, showing that their model correctly predicts IG spreads, while underpredicting HY spreads. They do however use different definitions of the leverage rations, with Bai et al. (2020) using the market value of debt, while Feldhütter and Schaefer (2018) use book value. Clearly, there is disagreement on this field, and we therefore include the leverage ratio as a variable in our regression. We use the same definition as Feldhütter and Schaefer (2018) and define the leverage ratio as the book value of debt / market value of equity + book value of debt.

$$\text{Leverage ratio} = \frac{\text{Book value of debt}}{\text{Market value of equity} + \text{Book value of debt}} \tag{2.15}$$

We include the market capitalization as a proxy for size premium in the bond market. Sæbø (2011) argues that larger issuers tend to have lower spreads than smaller issuers due to perceived stability. Thus, we expect the model to explain more of the spreads, indicating a negative coefficient when having the absolute credit spread puzzle as our dependent variable.

J. Z. Huang and Huang (2012) show that the credit spread explained by the model decreases for bonds of shorter maturities. Consequently, we expect a positive relationship between increased time-to-maturity and mispricing, and include time-to-maturity as a variable.

Market sentiment variables

Incorporating the VIX Index in our analysis, we leverage its role as a gauge for expected market volatility and sudden marked changes, also known as jump-risk. Kwon (2020) underscores the VIX's effectiveness in tracking risk shocks, linking it closely with credit spread movements and its broader impact on financial markets. Known as the 'fear index', the VIX measures anticipated 30-day market volatility, calculated from the implied volatility of S&P 500 index options, thus reflecting market sentiment and uncertainty (Whaley, 2009). Cremers et al. (2008) use a a different measure of jump-risk. However, we include the VIX Index as it captures the forward-looking aspect of market volatility and its impact on the absolute mispricing.

In our analysis, we include the Brent Spot as a proxy for oil price, recognizing its significance as an indicator of business cycle risk in the Norwegian market. This approach aligns with the broader perspective of Chen (2010), highlighting the impact of macroeconomic fluctuations on credit markets. Additionally, our study revisits Sæbø (2011)'s findings, which during 2008-09 did not conclusively establish a correlation between oil prices and market risk premiums. Given the considerable volatility in oil prices over the last ten years, we aim to explore its influence on credit spreads within the current context.

Liquidity variables

Our first measure of market liquidity is the price impact measure used by Dick-Nielsen et al. (2015). The price impact metric is used to quantify the effect an individual trade has on the market price. For the measurement to be calculated, a bond needs to be traded at least twice within a specified period. If successive trades do not significantly affect the price, it would indicate a liquid market. Conversely, a substantial impact between trades is often a sign of market illiquidity. The measure follows many aspects of Amihud (2002) illiquidity measure, which is a liquidity measure commonly used in OTC markets as it has a modest data requirement.

Where Amihud (2002) measures price reaction as a response to trading volume, Dick-Nielsen et al. (2015) find no positive linear between trading volume and price impact. Their approach does therefore not include trade volume in the price impact measure.

In the following, we will present the calculation of the price impact measure. For each transaction, the price impact, PI, is defined as:

$$PI_{i,t,k} = \frac{|p_{i,t,k} - p_{i,t,k-1}|}{p_{i,t,k}} \times 10000 \tag{2.16}$$

Here, $p_{i,t,k}$ is the trading price of transaction k in each month for bond i in month k. We multiply the fraction by 10,000 to interpret the measure in basis points. Furthermore, the absolute value of the price fluctuation is used to quantify the magnitude of the movement, irrespective of its direction.

We define a monthly price impact measure for each bond, which is calculated as the average price impact for each bond in the given month.

$$PI_{i,t} = \frac{1}{N} \sum_{k=1}^{N} PI_{i,t,k} \tag{2.17}$$

Here, N is the number of price impact observations in month t for bond i.

Finally, to calculate the monthly price impact measure, we sum the weighted monthly price impact measures, where the weights are the amount outstanding in the given bond.

$$PI_t^{Market} = \frac{1}{o_1 + \ldots + o_M} \sum_{i=1}^{M} o_i \times PI_{i,t} \tag{2.18}$$

Where o_i is the amount outstanding for bond i, and is constant for each bond across periods. M is the number of separate bonds traded in the market in month t. The influence of price impacts is adjusted based on the size of the bonds, giving greater significance to the effect of larger bonds on market price impact compared to smaller bonds.

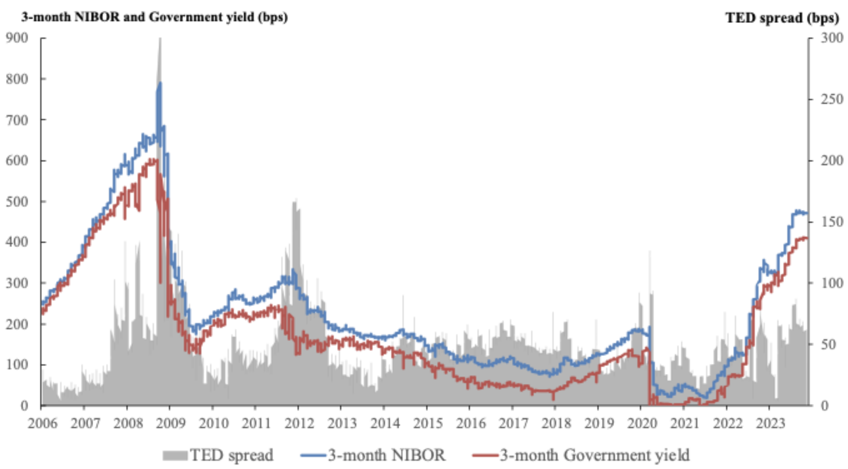

Figure 2.2: TED spread over time

Further, we incorporate the TED spread as a measure of market liquidity. Specifically for the Norwegian context, we calculate the TED spread as the differential between the 3-month NIBOR and the yield on 3-month government bonds. Presented in Figure 2.2, the spread marked in grey serves as an indicator of short-term interbank lending risks, encompassing both credit and liquidity aspects Brunnermeier (2009). Notably, in periods of market stress, there is a tendency for investors to shift towards safer assets such as government bonds. This flight-to-quality behavior typically results in an elevated TED spread, signifying heightened market illiquidity(Sundaresan, 2009). Hence, we expect a positive coefficient leading to increased spreads deviation from the default risk. Based on Sæbø (2011), we have included the bond size to assess the liquidity of each specific bond. We believe that larger bond issues are more liquid; hence, we expect a negative coefficient.

2.7.2 Pooled OLS Regression

In our analysis, we follow existing literature regarding the use of the regression model. Dick-Nielsen et al. (2012) and Sæbø (2011) analyze the transaction data as panel data using a Pooled Ordinary Least Squares (POLS) model in their regressions. Certain critical assumptions must be met to yield reliable and efficient estimates from the POLS model. Wooldridge (2019) outlines these assumptions in detail, which are comprehensively outlined in Appendix A.

In our regression model, we study our dependent variable, Absolute Mispricing, which is the difference between the actual spread and the model-derived default spread for each transaction. We regress this mispricing against the N different independent variables, x_n, described in section 2.7.1 using the POLS to determine the coefficients β_n. The model is presented in the following equation:

$$\text{Absolute Mispricing}_{i,n} = \beta_0 + \sum_{n=1}^{N} \beta_n x_{in} + \epsilon_{it} \tag{2.19}$$

where i is the unique ISIN and n is the transaction number, measured from oldest to newest. $\epsilon_{it} = \alpha_i + v_{it}$ is the error term, where α_i is unobserved time-constant heterogeneity and v_{it} is unobserved time-varying heterogeneity.

When analyzing panel data, which varies over time, it is essential to consider the potential for autocorrelation and heteroscedasticity in the error term of equation 2.19.

Autocorrelation refers to a correlation between error terms across periods for a given ISIN, which can lead to biased and unreliable estimates. Heteroscedasticity is characterized by a non-constant variance of the error term, which violates the homoscedasticity assumption in POLS and further complicates the results if not accounted for (Wooldridge, 2019). To identify these issues and deal with potential violations of the OLS assumptions, we use an autocorrelation plot to visually assess the presence of autocorrelation in the residuals a residual plot to inspect the level of heteroscedasticity.[7] Additionally, there could be an ISIN-level correlation. We follow Dick-Nielsen et al. (2012) and apply two-way clustered standard errors in our regressions to adjust for these biases. We also conduct a Variance Inflation Factor (VIF) test and a correlation matrix to detect any potential multicollinearity in our model. Multicollinearity occurs when the independent variables are inter-correlated, leading to inflated standard errors and misleading statistical significance. However, the results indicate that there is no evidence of multicollinearity in our model.[8]

[7] See Appendix B.
[8] See Appendix C.

3 Data

In this chapter, we introduce our data sources, delineate the criteria for sample selection, and provide a summary of the descriptive statistics of our data set. In section 3.1, we identify the origins of our data. In section 3.2, we then elaborate on our selection methodology, detailing our inclusion and exclusion criteria to ensure the robustness and relevance of our sample. In section 3.3, we present descriptive statistics highlighting the primary attributes of our data set.

3.1 Data Sources

The data used in this study is sourced from various providers, detailed in the following sections. We also collect additional data from Datastream, such as market capitalization and book value of debt. Key market indicators like the VIX Index, Brent Spot prices, and interest rates, including swap rates, NIBOR, and government bond yields, are obtained from Bloomberg.

3.1.1 Transaction Data

We obtain transaction data for the Norwegian corporate bond market through Nordic Bond Pricing, a trusted market provider of evaluated bond prices. With permission from Euronext Oslo Stock Exchange, Nordic Bond Pricing provided us with all bond transactions registered over the Oslo Stock Exchange and the Nordic ABM from May 2014 until November 2023. In total, the data from Nordic Bond Pricing Consisted of 269,653 fixed-income transactions. The data included the traded price of each bond transaction, which was a crucial input in our calculation of actual spreads.

3.1.2 Bond Reference Data

From Nordic Trustee, we gather data about bond characteristics from the Norwegian fixed-income market. Access to the Stamdata database allowed us to gather information on all relevant bonds. This data includes issue and maturity dates, coupon rates, redemption type, industry, rating, and other bond characteristics.

3.1.3 Expected Default Frequencies (EDFs)

With permission from Moody's, we gathered default probabilities through Folketrygdfondet. The data includes files for every date from 31.12.2013 until 13.11.2023. Further, for each date, there was data about every publicly traded firm in the Moody's universe. This data consisted of all the input parameters that went into the Estimated Default Frequency calculations, as well as the estimated default probabilities themselves. For each date, each firm had the estimated cumulative probabilities that it would default within the next years, ranging from 1 to 10 years. In that way, for every transaction, we gathered the default probabilities for the issuing firm on the transaction date.

Further, from the 10 estimated probabilities, we constructed an "estimated default probability curve" through interpolation, like for the yield curve. Using the time-to-maturity on the trade date, we could plot the time-to-maturity on the curve. As a result, for every observation, we had an estimated cumulative probability that the firm would default on its debt obligations within a time frame that was equal to the time-to-maturity of the bond on the transaction date.

On some dates, the files from Moody's lacked the required data. Over a 10-day period in June 2015, there was no data for the firms for which we gathered information. As a result, we had to delete all transactions over this period from our sample, totalling 189 transactions. For dates with missing values, but when the next business day was available, we used the values of the next day as proxies for the missing values. In total, this was done to estimate default probabilities for 128 transactions. Considering our total sample of 30,647 transactions, we are not concerned that these operations have affected the validity of our results.

3.2 Sample Selection

From Nordic Bond Pricing, we obtained transaction data from 12.05.2014. Therefore, this served as a natural starting point for our analysis. Although we initially wanted to conduct our analysis over an even more extended period, considering that one of our main goals was to examine the credit spread puzzle from 2015, the time frame from 2014 to 2023 was deemed satisfactory.

We made several operations to our sample to make it suitable for our analysis. First, we only included senior unsecured bonds. The major difference between a senior unsecured bond and a senior secured bond is that a secured bond has a specific collateral guaranteeing it Berk and DeMarzo (2023). Therefore, including these bonds would require valuation and estimation of volatility on the collateral to be able to determine a correct model spread. Consequently, only senior unsecured bonds, where the values of the whole asset base of the issuing company determine the spreads, were included. This significantly reduced the number of transactions, as many bonds were senior secured, especially.

Furthermore, only bonds in NOK with a Norwegian issuer were included. This was done to prevent any currency effects or foreigner premiums/discounts, which could have affected the validity of our results. Only bullet bonds, where the entire principal amount is paid at maturity, were included. In addition, all bonds with any optionality included in them were removed, as options may affect the price away from the true value of the underlying bond. Lastly, we only include issuers with listed equity, thus excluding savings banks.

3.3 Descriptive Statistics

We were left with a sample of 30,647 senior unsecured bond transactions. Our observations range from May 2014 to mid-November 2023. As shown in Table 3.1, the industrial, oil, and shipping sector has the most transactions in our sample, both across the entire span and within all the defined periods.

Table 3.1: Number of transactions per sector per period

Sector	**Total**	**2014-16**	**2017-19**	**2020-23**
Financial	9,428	2,306	3,200	3,922
Industrial, Oil and Shipping	16,046	6,945	4,269	4,832
Miscellaneous	5,149	1,444	1,239	2,466
Utilities	24	20	4	0
Total	30,647	10,715	8,712	11,220

Table 3.2: Number of unique issuers per sector per period

Sector	Total	2014-16	2017-19	2020-23
Financial	8	5	8	6
Industrial, Oil & Shipping	30	25	18	17
Miscellaneous	20	13	12	13
Utilities	2	2	1	0
Total	60	45	39	36

Table 3.2 illustrates the transaction activity by showing the number of unique issuers within each period. The industrial, oil, and shipping sector has the most issuers in our bond data, which is not surprising, given their significant contribution to the growth of the Norwegian economy and the scale of the high-yield bonds within the credit market. The tables also show that the financial sector, especially banks, has many transactions relative to its few unique issuers. On the other hand, utilities have a negligible effect on the overall market. Because of this, we choose to include their transactions in the miscellaneous category in our further analysis.

Table 3.3: Descriptive statistics for observed credit spreads (bps)

Variable	N	Mean	Median	Min.	P25	P75	Max.
Sector							
Financial	9,428	55	47	-130	31	68	293
Industrial, Oil & Shipping	16,046	567	368	-134	238	537	9,850
Miscellaneous	5,173	231	173	-38	81	327	1,547
Time-to-maturity							
Below 1 year	4,775	224	72	-130	27	240	9,477
1-3 years	14,550	364	181	-134	50	374	9,850
3-5 years	9,152	404	296	18	100	460	8,003
Above 5 years	2,170	344	271	48	100	562	1,625
Issue Risk							
HY	13,890	640	400	-127	301	555	9,850
IG	16,757	115	65	-134	40	122	1,054
Risk Class							
Finance	9,428	55	47	-130	31	68	293
Non-Financial Company	21,219	485	324	-134	182	495	9,850
Total	30,647	353	204	-134	60	406	9,850

Table 3.3 illustrates the descriptive statistics for the observed credit spread in basis points based on sector, the remaining time-to-maturity on the trade date, issue risk, and risk class. Our sample distribution tends towards right-skewed data because of large spreads within

the high-yield bonds, especially those within the industrial, oil and shipping sector. These outliers significantly affect the average spreads, leading us to look at the median spreads as more representative across the sample. Based on sector, we observe that industrial, oil and shipping have the highest number of transactions, while financial has the lowest. This is due to the latter only issuing investment-grade bonds, while a significant fraction of industrial, oil and shipping are categorized as high-yield bonds. Studying the spreads based on remaining time-to-maturity, we observe lower spreads on transactions with shorter time-to-maturity. The spreads increase with time-to-maturity, indicating a higher risk for bonds with longer durations due to increased default risk and volatility over a longer horizon.

Tables 3.4 and 3.5 present the distribution of transactions and issuers within each sector based on remaining time-to-maturity. According to the tables, bonds with a maturity between 1-3 years have the highest number of transactions and issuers. As the bond maturity increases, there is a significant decrease in both transactions and issuer presence.

Table 3.4: Number of transactions per sector by time-to-maturity

Sector	**Total**	**$<$ 1 year**	**1-3 years**	**3-5 years**	**$>$ 5 years**
Financial	9,428	1,980	5,012	2,082	354
Industrial, Oil and Shipping	16,046	1,932	7,222	5,649	1,243
Miscellaneous	5,173	863	2,316	1,421	573
Total	30,647	4,775	14,550	9,152	2,170

Table 3.5: Number of issuers per sector by time-to-maturity

Sector	**Total**	**$<$ 1 year**	**1-3 years**	**3-5 years**	**$>$ 5 years**
Financial	8	7	7	6	4
Industrial, Oil and Shipping	30	24	29	26	14
Miscellaneous	22	15	18	16	15
Total	60	46	54	48	27

4 Results

In this chapter we present our results based on the first two objectives in our thesis. First, we present of and to what extent the credit spread puzzle exist. Based on the results in the first section, we show which additional risk premiums investors are compensated for beyond the default risk.

4.1 Measuring the Extent of The Credit Spread Puzzle

The result section begins with a comparison of the model estimates to the actual spreads observed. At this stage, we examine the different spread types at an aggregate level without directly linking them to their counterparts. Table 4.1 provides the median spread for each sector in different periods. We have opted to present median numbers due to significant outliers, notably within oil service and shipping between 2014-2016.

Table 4.1: Median credit spreads (bps)

Sector	**Spread Type**	**Total**	**2014-16**	**2017-19**	**2020-23**
Finance	Actual	47	51	46	47
	Model	23	26	27	19
Industrial, Oil & Shipping	Actual	368	503	286	299
	Model	60	144	51	35
Miscellaneous	Actual	173	293	110	147
	Model	27	19	35	29
Total	Actual	204	388	105	126
	Model	35	66	34	26

When observing the entire period, there is a noticeable and significant mismatch between the actual spreads observed in the market and our model's spreads. Our model predicts a median spread of 35 bps, while the actual spread observed in the market has a median value of 204 bps. Hence, our model significantly underestimates the level of credit risk compared to what bond investors in Norway demand.

The disparity is the most severe within the industrial, oil and shipping sector, despite this sector having the highest median model spread. In contrast, the finance sector has the most matching spreads, with the model predicting a credit spread of 23 bps while the market spread is 47 bps. Interestingly, even with a similar model spread of 27 bps, the miscellaneous column has a significantly higher actual spread of 173 bps.

When examining the variations between periods, it becomes evident that both spreads show a decreasing trend over time. Notably, the median actual spread has seen a substantial reduction, from 388 bps between 2014 and 2016 to 126 bps after the turn of the decade. The model spread has also seen a reduction from 66bps to 26bps. However, it has not decreased as much as the actual spreads, neither in absolute nor relative terms.

Assessing time variations at a sector level reveals noteworthy disparities. The actual and model spreads have remained relatively stable within the financial sector. In contrast, for non-financial companies, there has been a significant decline in actual spreads. For industrial, oil and shipping, the decline is mirrored by a fall in model spreads. However, for the miscellaneous sector, the downfall in actual spreads does not correspond with the development in model spreads, which have remained consistently low throughout the whole period. A notable illustration of the disparity in spread dynamics for this sector can be seen when comparing the first and second periods. During this time, the median actual spread fell considerably, plummeting from 293 bps to 110 bps. In contrast, model spreads experienced the opposite trend, rising from 19 bps to 35 bps, presenting an intriguing divergence.

In the subsequent section, we refine the presentation of our results by pairing each actual spread estimate with the corresponding model spread. We study the explained share accounted for by the model, expressed as percentages in Table 4.2. Beyond analyzing the median explained share, we also compute the interquartile range, from the 25th to the 75th percentile, to gauge the level of uncertainty around the median.

Table 4.2: Median explained share per sector over time

Period	**Total**		**2014-16**		**2017-19**		**2020-23**	
Sector	Median	IQR	Median	IQR	Median	IQR	Median	IQR
Financial	51	(38-69)	49	(40-65)	61	(48-78)	43	(31-59)
I, O, and S	17	(9-32)	21	(10-41)	18	(11-30)	13	(7-23)
Miscellaneous	19	(6-40)	8	(3-30)	26	(10-52)	19	(9-47)
Total	**28**	**(12-52)**	**28**	**(11-49)**	**32**	**(14-60)**	**25**	**(11-47)**

Overall, the model's median explained share measured over the whole time period is 28 percent. The interquartile range shows a 12 to 52 percent spread, indicating relative stability in the model's performance. Across various time periods, the explained share shows notable consistency, with the central value hovering closely around 28 percent.

An analysis of different sectors also reveals temporal stability. Generally, the explained share is much higher for financial companies than non-financial companies. Specifically, for financial firms, the explained share peaked at 63 percent during the second period and then declined to 43 percent in recent years. For industrial, oil and shipping companies, it was initially highest at 21 percent, when both the actual spreads and model spreads were elevated, before falling to a mere 13 percent over the last four years. The explained share is at 19 percent in the miscellaneous sector, but this figure masks fluctuations across time intervals. Moreover, in this sector group, the interquartile range also suggests the most significant uncertainty around the median value.

Table 4.3: Median absolute mispricing per sector over time

Period	**Total**		**2014-16**		**2017-19**		**2020-23**	
Sector	Median	IQR	Median	IQR	Median	IQR	Median	IQR
Financial	21	(11-36)	23	(14-39)	16	(9-26)	24	(13-47)
I, O, and S	264	(156-397)	341	(213-541)	218	(122-296)	236	(122-345)
Miscellaneous	137	(30-303)	260	(56-417)	73	(20-235)	92	(30-252)
Total	**143**	**(50-284)**	**269**	**(92-337)**	**95**	**(29-222)**	**120**	**(49-232)**

In our analysis of absolute mispricing, shown in Table 4.3, the median across the whole sample is 143 basis points, calculated by subtracting the model spread from the actual spread. Opposed to the relative measure, this metric varies significantly between different periods. From 2014 to 2016, when actual spreads peaked, the mispricing reached 269 basis points. This figure then substantially decreased to 95 basis points between 2017 and 2019, followed by a slight uptick in the subsequent period. The interquartile analysis reveals two key insights: First, the 25th percentile in the first period is on comparable levels as the median in the second, supporting the view that the mispricing was generally higher in the first period. Secondly, from 2014 to 2016, the median of 269 bps is much closer to the 75th percentile of 337 bps than the 25th percentile of 92 bps. This indicates that 25 percent of observations in this time frame had absolute mispricing within the relatively tight range of 269 bps and 337 bps, a narrow window.

An examination of absolute mispricing across sectors also yields insight. In the financial sector, the absolute mispricing displays stability over time, hovering around the median of 21 basis points. This trend mirrors the patterns observed in the explained share analysis. Conversely, the industrial, oil and shipping sector exhibits substantially higher mispricing on 264 basis points. Its peak mispricing reached 341 basis points between 2014 and 2016, coinciding with the actual spread's peak of 503 basis points. In the subsequent periods, mispricing decreased to 218 and 236 bps, respectively. In the miscellaneous sector, there are considerable time variations around the overall mispricing of 137 basis points. The median mispricing was notably high at 260 bps in the first period, then fell considerably to 73 and 92 basis points in later periods. This trend aligns with the notable increase in explained share for this sector.

We use the remaining time-to-maturity of bonds as a proxy for liquidity under the assumption that longer-maturity bonds are generally less liquid than shorter-maturity ones. Our analysis reveals that the explained share, in all sectors, varies little with time to maturity. However, a notable exception emerges for maturities exceeding 5 years, especially in the financial and miscellaneous sectors. Here, we observe substantial increases in the explained share. The rise could be influenced by the limited number of transactions for bonds with maturities over 5 years, as showed in Table 3.4. Consequently, the data for maturities beyond 5 years might reflect a specific subset of issuers, potentially leading to a bias.

Table 4.4: Median explained share by sector and time-to-maturity

Sector / Years to Maturity	**0-1**	**1-2**	**2-3**	**3-5**	**5+**
Financial	50%	46%	51%	57%	69%
Industrial, Oil and Shipping	18%	15%	16%	18%	19%
Miscellaneous	12%	24%	21%	14%	47%
Total	**33%**	**29%**	**29%**	**24%**	**30%**

Our examination of absolute mispricing in Table 4.5 reveals a distinct upward trend in mispricing for longer maturities. Across all sectors, the mispricing escalates from 43 basis points for the shortest maturity bonds to 234 basis points for maturities between 3 and 5 years. However, this trend reverses for bonds with the longest maturities, where a significant decline in mispricing is observed.

Specifically, in the financial sector, the increase in mispricing is modest in absolute terms. Despite an upward trajectory, the mispricing growth remains slightly measured in absolute terms. Although there is a clear upward trend, the increase is minor. The industrial, oil and shipping sector exhibits a steady rise in mispricing with longer maturities, maintaining elevated levels in the longest maturity bracket. Conversely, the miscellaneous sector

Table 4.5: Median absolute mispricing by sector and time-to-maturity

Sector / Years to Maturity	**0-1**	**1-2**	**2-3**	**3-5**	**5+**
Financial	12	19	24	27	21
Industrial, Oil and Shipping	143	224	260	311	313
Miscellaneous	118	116	198	175	61
Total	**43**	**80**	**136**	**234**	**99**

displays a sharp decrease in mispricing for bonds with maturities exceeding 5 years. However, this number may reveal a potential bias, as the number of unique issuers fall is lower in this category.

4.2 Investigating the Determinants of Credit Spread Mispricing

In section 4.1, we looked at the distinction between the actual and the model credit spread using our structural model. Based on the results, we observe that the median default risk only accounts for 28 percent of the total credit spread. Based on this, we will in this part investigate what other factors that contribute to this mispricing. Our findings is based on the Pooled Ordinary Least Squares (POLS) regression analysis described in section 2.7.2, which considers the factors that influence the absolute mispricing. To acquire an understanding of the variables beyond credit risk that impact the spreads, we first present the univariate regression results. Then we present our main regression model in Table 4.7 to study the variables effect on each other in explaining the puzzle. Further, we examine the regressions based on sector and periods to show how the included variables changes between sectors and over time.

4.2.1 Univariate Regression

In the presented univariate regression analysis in Table 4.6, distinct factors exhibit varying degrees of influence on credit spread mispricing. The positive coefficients for the industrial, oil and shipping and miscellaneous sectors indicate a higher degree of mispricing compared to the financial sector, which serves as the baseline. The sector category as a whole explains about 11 percent of the variance in mispricing, as indicated by an adjusted R-squared of 0.111.

Regarding bond-specific characteristics, market capitalization inversely affects mispricing, with larger firms experiencing less mispricing. The firm size have a relatively high R-squared, explaining 12.7 percent of the variation in relative mispricing. On the over side, the leverage ratio presents a negative correlation with mispricing, but does not seem to be a large factor in explaining the mispricing compared to the market capitalization with an adjusted R-squared of 0.5 percent. The time-to-maturity shows a positive association with mispricing, indicating that bonds with longer durations are generally mispriced. However, isolated it has little explanatory power.

Liquidity metrics, namely the price impact measure and the TED spread, exhibit a direct relationship with mispricing, reinforcing the significance of liquidity in the pricing of credit spreads. Larger bond issues correlate with less mispricing, as indicated by the negative coefficient for bond size. Also here, the liquidity measures alone has little explanatory power represented by low adjusted R-squared.

The market sentiment, as indicated by the VIX Index, exhibits a negative coefficient with absolute mispricing, demonstrating a limited influence with an adjusted R-squared of just 0.02 percent. Similarly, the oil price has a negative coefficient, suggesting that higher oil prices are associated with reduced mispricing.

In sum, the univariate regression underscore sector risk and firm size as prominent factors in credit spread mispricing, with the financial sector exhibiting the least absolute mispricing. The adjusted R-squared values indicate that while some factors have a substantial explanatory power, others contribute less to the overall variability in mispricing.

Table 4.6: Univariate regression results on absolute mispricing

Category	**Variable**	**Coefficient**	**t-stat**	**Adj. R^2**
Sector	Financial	27.6***	42.3	
	Industrial, Oil And Shipping	372.5***	38.6	0.111
	Miscellaneous	139.2***	34.5	
Bond-specific	log(Market Cap)	-123.2***	-38.1	0.127
	Leverage Ratio	-204.7***	-16.9	0.005
	Time-to-Maturity	22.3***	17.9	0.005
Liquidity	Price Impact	7.6***	16.7	0.018
	TED spread	2.6***	17.4	0.012
	log(Bond Size)	-98.1***	-22.1	0.005
Market sentiment	VIX	-1.0***	-3.2	0.0002
	Oil Price	-3.3***	-27.6	0.018

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

4.2.2 Entire Sample Results

The main regression results are presented in Table 4.7. Sector dummies are included in every regression model to account for the unique characteristics of different industries that may impact the dependent variable. Statistically, the sector dummies' coefficients measure the relative difference in absolute mispricing for bonds in each sector compared to those in the financial sector, which serves as the baseline. A positive coefficient for a sector indicates higher absolute mispricing relative to the financial sector, while a negative coefficient suggests lower mispricing. By incorporating sector dummies, the model can isolate the impact of other variables and accurately account for these inherent differences between sectors.

Table 4.7: Regression results on entire sample

	Dependent variable:						
	Absolute Mispricing						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	27.572***	1,723.601***	1,355.502***	14.140***	22.634**	220.907***	1,725.549***
	t = 42.605	t = 13.143	t = 8.386	t = 3.278	t = 2.051	t = 16.342	t = 9.276
Industrial, Oil And Shipping	372.445***	381.028***	356.135***	368.979***	372.697***	366.067***	359.958***
	t = 38.615	t = 25.606	t = 39.494	t = 36.189	t = 39.345	t = 39.458	t = 22.533
Miscellaneous	139.175***	247.598***	121.562***	136.173***	139.193***	142.091***	226.463***
	t = 34.537	t = 14.764	t = 29.758	t = 32.452	t = 34.536	t = 35.121	t = 12.808
log(Market Cap)		−90.434***					−87.838***
		t = −16.400					t = −15.992
Leverage Ratio		520.877***					477.141***
		t = 10.603					t = 9.185
Price Impact			6.127***				3.378***
			t = 8.060				t = 4.224
TED spread			1.583***				0.773***
			t = 6.669				t = 3.397
log(Bond Size)			−68.966***				−3.668
			t = −8.898				t = −0.517
Time-to-Maturity				5.989***			13.232***
				t = 3.137			t = 7.291
VIX Index					0.262		0.772
					t = 0.440		t = 1.457
Oil Price						−2.884***	−0.726***
						t = −14.145	t = −3.612
Observations	30,647	30,647	30,647	30,647	30,647	30,647	30,647
R^2	0.111	0.221	0.133	0.112	0.111	0.125	0.230
Adjusted R^2	0.111	0.221	0.133	0.111	0.111	0.125	0.230
Note:							*p<0.1; **p<0.05; ***p<0.01

Our results in Table 4.7 reveal that credit spread mispricing is largely determined by sector risk and size premium. The results of the sector analysis show that there are significant differences in mispricing across different sectors, with the financial sector having notably lower mispricing compared to the industrial, oil, and shipping sectors.

Moreover, the negative coefficient of the market capitalization indicates that size premium is a crucial factor, with larger firms exhibiting significantly lower mispricing. Compared to the univariate regression in Table 4.6, the size of the bond issuer explains a significant part of the absolute mispricing. The mispricing also seem to increase with longer time-to-maturity on bonds.

In contrast, liquidity factors, represented by the price impact measure and TED spread, demonstrated a statistically significant impact at the 1 percent level. However, their contribution to the model's explanatory power is relatively minor. When controlling for sectors, the increase in adjusted R-squared attributable to these liquidity measures is only 2.2 percent. Separately, the time-to-maturity shows a notable influence on mispricing. The VIX Index does not significantly impact mispricing when studying the entire sample. On the other hand, controlling for sectors, the coefficient of oil prices is significantly negative and increases the adjusted R-squared by 1.4 percent.

4.2.3 Mispricing across sectors

To further investigate the determinants of the puzzle between sectors, we present the regression results in Table 4.8.

Within the financial sector, larger firms, as indicated by the positive coefficient for market cap, are associated with reduced mispricing. Conversely, in the industrial, oil, and shipping sector and the miscellaneous sector, a negative coefficient for market cap indicates increased mispricing for larger firms.

The interpretation of the leverage ratio also varies across sectors. In the financial sector, a negative correlation with the mispricing signifies that higher leverage does not necessarily lead to increased mispricing. However, the industrial, oil, shipping, and miscellaneous sectors exhibit a positive correlation between the leverage ratio and the mispricing, implying a heightened sensitivity to leverage-related risks in these sectors.

The bond size negatively correlates with the mispricing in the financial and miscellaneous sectors. In contrast, this relationship is not evident within industrial, oil and shipping. In terms of market liquidity, the TED spread shows a higher significance in the financial sector than in the others.

Table 4.8: Regression results based on sector

	Dependent variable: Absolute Mispricing								
	Financial			Industrial, Oil and Shipping			Miscellaneous		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	19.699^{***}	37.404^{***}	283.891^{***}	363.656^{***}	726.451^{***}	$3{,}156.973^{***}$	187.527^{***}	250.927^{***}	$1{,}268.147^{***}$
	t = 26.477	t = 11.695	t = 12.950	t = 21.783	t = 24.057	t = 7.805	t = 33.387	t = 16.891	t = 7.053
log(Market Cap)			0.678^{**}			-129.861^{***}			-41.002^{***}
			t = 2.489			t = −15.953			t = −5.749
Leverage Ratio			-264.352^{***}			690.249^{***}			145.740^{***}
			t = −10.060			t = 7.637			t = 5.488
Price Impact			0.585^{***}			4.920^{***}			1.630^{***}
			t = 10.905			t = 3.431			t = 5.696
TED spread			0.394^{***}			1.147^{**}			0.582^{*}
			t = 11.070			t = 2.444			t = 1.783
log(Bond Size)			-3.989^{***}			−16.874			-15.930^{***}
			t = −8.217			t = −0.979			t = −3.861
VIX Index			0.957^{***}			1.169			2.927^{***}
			t = 11.965			t = 1.084			t = 2.787
Time-to-Maturity	3.510^{***}		3.982^{***}	12.887^{***}		18.216^{***}	-7.573^{***}		3.503^{***}
	t = 11.372		t = 15.536	t = 3.710		t = 4.957	t = −5.409		t = 3.095
Oil Price		-0.147^{***}	0.011		-5.036^{***}	-1.299^{***}		-1.237^{***}	−0.033
		t = −3.320	t = 0.451		t = −13.588	t = −3.535		t = −5.895	t = −0.124
Observations	9,428	9,428	9,428	16,046	16,046	16,046	5,173	5,173	5,173
Adjusted R^2	0.030	0.011	0.357	0.001	0.025	0.184	0.008	0.032	0.296

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The expected market volatility and jump-risk, as measured by the VIX Index, positively influences the mispricing in the financial and miscellaneous sectors. Notably, the oil price exhibits a significant negative correlation with the mispricing within industrial, oil and shipping when including all risk factors.

The explanatory power of our models varies across sectors. The financial sector demonstrates the highest adjusted R-squared at 35.7 percent, indicative of the model's effectiveness in capturing mispricing variations for financial issuers. The industrial, oil, and shipping sector presents a lower adjusted R-squared value of 18.4 percent, while the miscellaneous sector has an adjusted R-squared of 29.6 percent.

4.2.4 Mispricing across periods

In this analysis, we scrutinize the results across three distinct periods, as outlined in Tables 4.9-4.11, focusing on the evolution of risk premiums over time.

For the period-specific Model 1, which estimates sector risk, all sectors display significant positive contributions across each period. Notably, the sector's explanatory power peaks in 2020-23 with an adjusted R-squared of 32 percent, compared to a 9-10 percent range in the earlier periods.

In assessing market capitalization, its impact remains negative and significant across all periods, suggesting a persistent size risk premium. The magnitude of this premium, as reflected in the incremental adjusted R-squared, is more pronounced in 2014-16 (11 percent) and 2017-19 (13.9 percent), tapering to 2.9 percent in 2020-23.

With its positive and significant coefficients across all periods, the leverage ratio highlights a uniform trend of increased mispricing with higher leverage.

Liquidity measures, particularly the price impact measure and TED spread, demonstrate heightened significance in 2020-23. In this period, the liquidity measures add an additional adjusted R-squared of 6.5 percent when accounting for sector risk, underlining a stronger correlation between reduced market liquidity and increased mispricing.

Time-to-maturity, evaluated in Model 4, reveals varied trends. 2014-16 is not statistically significant, whereas 2017-19, longer maturities correlate with lower mispricing. Conversely, in 2020-23, we see a positive and significant association, indicating increased mispricing for longer maturities.

The VIX Index's role, assessed in Model 5, stands out in 2020-23 with significant influence and a 10 percent increase in adjusted R-squared when considering sector risk. This starkly contrasts with earlier periods where its impact was less pronounced.

Finally, examining Model 7, which integrates all variables, the 2020-23 period showcases the highest explanatory power, elucidating 46 percent of the variance in absolute mispricing. This elevated level is predominantly influenced by sector risk and heightened market volatility, as the VIX Index indicates. The size premium risk is notably significant and positive in the first two periods. The influence of oil prices is significant only in the

2014-16 model.

These findings articulate a dynamic interplay of factors influencing credit spread mispricing, with each period manifesting distinct risk premiums and sector influences.

Table 4.9: Regression results 2014-16

	Dependent variable:						
	Absolute Mispricing						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	26.557***	2,752.873***	2,798.332***	32.995***	−37.466	299.222***	5,722.835***
	t = 28.255	t = 11.365	t = 5.585	t = 3.253	t = −1.124	t = 15.683	t = 9.692
Industrial, Oil And Shipping	517.101***	387.535***	481.157***	519.179***	516.147***	505.226***	308.978***
	t = 28.265	t = 25.358	t = 29.674	t = 25.130	t = 27.958	t = 28.305	t = 16.995
Miscellaneous	208.334***	189.816***	144.887***	208.443***	206.360***	183.007***	110.403***
	t = 45.094	t = 10.048	t = 13.268	t = 45.078	t = 43.514	t = 27.940	t = 5.196
log(Market Cap)		−136.351***					−138.599***
		t = −12.430					t = −13.211
Leverage Ratio		564.273***					560.795***
		t = 8.132					t = 8.168
Price Impact			6.222***				3.165*
			t = 4.686				t = 1.948
TED spread			2.023*				2.577***
			t = 1.839				t = 2.665
log(Bond Size)			−140.736***				−129.534***
			t = −6.005				t = −6.160
Trade_to_Maturity				−2.702			41.201***
				t = −0.636			t = 11.649
VIX Index					4.098*		−12.218***
					t = 1.910		t = −3.931
Oil Price						−4.247***	−4.361***
						t = −14.211	t = −9.692
Observations	10,715	10,715	10,715	10,715	10,715	10,715	10,715
Adjusted R^2	0.099	0.209	0.117	0.099	0.100	0.119	0.242
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 4.10: Regression results 2017-19

	Dependent variable:						
	Absolute Mispricing						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	19.197***	1,121.621***	272.514**	65.639***	63.534	54.688	−469.550
	t = 41.962	t = 4.262	t = 2.083	t = 6.054	t = 1.338	t = 0.696	t = −1.587
Industrial, Oil And Shipping	312.270***	491.422***	310.129***	318.646***	311.989***	312.393***	480.256***
	t = 19.521	t = 8.431	t = 18.769	t = 18.965	t = 19.388	t = 19.655	t = 7.873
Miscellaneous	126.232***	377.164***	122.475***	133.075***	125.151***	125.558***	377.760***
	t = 21.276	t = 7.006	t = 19.867	t = 22.303	t = 20.022	t = 20.657	t = 6.411
log(Market Cap)		−83.320***					−93.112***
		t = −9.612					t = −9.380
Leverage Ratio		967.248***					925.192***
		t = 5.417					t = 4.805
Price Impact			1.730				1.302
			t = 1.318				t = 1.105
TED spread			0.460				0.634
			t = 0.734				t = 1.261
log(Bond Size)			−13.470**				81.938***
			t = −2.167				t = 5.586
Time-to-Maturity				−19.614***			−2.363
				t = −4.276			t = −0.559
VIX Index					−3.101		0.312
					t = −0.933		t = 0.116
Oil Price						−0.560	1.983*
						t = −0.451	t = 1.678
Observations	8,712	8,712	8,712	8,712	8,712	8,712	8,712
Adjusted R^2	0.090	0.229	0.090	0.093	0.090	0.090	0.236

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

Table 4.11: Regression results 2020-23

	Dependent variable:						
	Absolute Mispricing						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	35.002***	32.685	172.149***	9.982***	−106.587***	95.830***	−179.159***
	t = 26.458	t = 0.715	t = 2.789	t = 3.206	t = −9.377	t = 6.268	t = −3.104
Industrial, Oil And Shipping	219.122***	279.293***	219.728***	214.234***	221.370***	218.294***	283.426***
	t = 38.790	t = 20.906	t = 38.837	t = 38.753	t = 38.517	t = 38.787	t = 21.374
Miscellaneous	102.035***	184.508***	103.764***	91.219***	111.621***	106.430***	183.887***
	t = 15.947	t = 10.352	t = 16.902	t = 13.850	t = 17.590	t = 15.856	t = 10.609
log(Market Cap)		−9.314***					−1.689
		t = −3.957					t = −0.704
Leverage Ratio		254.648***					257.911***
		t = 6.220					t = 6.628
Price Impact			4.417***				2.227***
			t = 5.893				t = 4.669
TED spread			0.658***				0.098
			t = 2.900				t = 0.622
log(Bond Size)			−9.208***				−6.846**
			t = −3.043				t = −2.306
Time-to-Maturity				12.154***			12.111***
				t = 8.526			t = 9.092
VIX Index					5.775***		4.393***
					t = 11.978		t = 10.654
Oil Price						−0.849***	0.224
						t = −4.036	t = 1.548
Observations	11,220	10,220	11,220	11,220	11,220	11,220	10,220
Adjusted R^2	0.320	0.349	0.385	0.331	0.420	0.333	0.460

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

5 Discussion

Regarding our first objective, the findings reveal a significant discrepancy between the actual spreads and those of our model, confirming the presence of a credit spread puzzle in Norwegian bond markets. With a median explained share of 28 percent, a significant 72 percent is still left unexplained by the credit model. Although the figure may seem low, it aligns with previous results the topic in Norwegian markets. Sæbø (2015) finds an average explained share of 28 percent measured from 2008-2013, while Langdalen and Johansen (2016) find a median explained share of 26 percent between 2003 and 2014. Our findings, with a median of 28 percent, are comparable to these numbers. It seems apparent that the credit model cannot account for all risk premiums the investors demand. We will next explore potential reasons behind the persistence of the credit spread puzzle using our results in Chapter 4.

5.1 Risk Premiums

5.1.1 Sector Risk premium

The research of Sæbø (2011) highlighted the significance of sector risk premiums influencing bond mispricing, particularly noting that differences between sectors could explain up to 46 percent of the variations in mispricing for 2008-2009. Our study's univariate regression analysis shows that sector classification accounted for 11.1 percent of mispricing observed. Although significantly lower than the figures of Sæbø, it nonetheless underscores that investors in the Norwegian bond market do consider sector risk premiums. Our results particularly point to the industrial, oil and shipping sectors experiencing the highest mispricing. There can be several different reasons for this.

First, as this sector consists of many oil, gas, and shipping firms, investors might demand a cyclicality premium. These industries are highly cyclical, with fluctuating oil, gas or freight prices significantly influencing earnings. For example, the dramatic fall in oil prices from over $100 to below $30 per barrel in 2015-2016 led to numerous defaults in the oil industry, and is still fresh in the memory of many Norwegian bond investors. Such events underline the persistent risks in these sectors, prompting investors to seek higher premiums to mitigate these risks. The sector premium could therefore be a result of an additional premium risk averse investors require for holding bonds of issuers in this sector.

Our model, which uses volatility measured over the last five years, does not in 2023 take the 2015 oil crisis into account in the calculation current default probabilities. This disconnect between the model and the market's risk perception, especially towards unexpected events or jump-risks, as highlighted by Chen (2010) and J. Z. Huang and Kong (2003), could also explain parts of why the industrial, oil and shipping sector consistently have the highest mispricing.

Another potential factor contributing to the mispricing in sectors like oil and gas is the risk associated with the potential phasing out of these energy sources. This sector now faces unique risks tied to climate change and alternative energy sources. As significant climate reports or breakthroughs in renewable energy could adversely affect these industries, the investors might demand a risk premium, especially for longer-term maturities. The regression models show that mispricing is notably affected by the time to maturity in this sector. This might suggest that investors are particularly concerned about extended commitments to this industry, perhaps due to the abovementioned risks.

The pronounced mispricing in the industrial, oil and shipping sector, which heavily features high-yield bonds, could also be attributed to a market-wide risk aversion towards this bond class, due to their high inherent risk, as noted by Sæbø (2015). Internationally, many institutional investors are constrained by their mandates to hold only investment-grade bonds, and reduced demand could therefore partly explain the mispricing in high-yield bonds. However, few investors in Norway are bound by such a mandate, making this explanation less applicable. The risk aversion towards high-yield bonds due to their inherent risk does, still, remain a possible explanation for the mispricing.

5.1.2 Size premium

Hwang et al. (2010) studied whether the systematic risk premiums Fama and French (1992) discovered for stock returns also were present in corporate bonds, and concluded that both the size and value factor were risk premiums reflected in bond prizes. Elton et al. (1999) also came to the same conclusion, and showed that spreads and returns vary for the same systematic factors as for stocks, suggesting that these risk premiums exist also in bond markets. Sæbø (2011) found that the size factor was a significant factor in the mispricing of Norwegian corporate bonds, and argues that it should be to no surprise to the market participants. The rationally behind the size factor is that investors show risk aversion toward smaller companies and therefore investing in smaller companies include a size risk premium, just as for stocks.

Our findings are very much in line with these previous studies with regards to the size premium. We find that companies with higher market capitalization tend to have considerably lower credit spreads. In fact, in the univariate regression, this independent variable proved to explain 17.2 percent of variations in absolute mispricing alone. The size factor remains negative when combining with other variables, strengthening the belief that the size premium exists in the Norwegian market. Initially, we suspected that the low figures could be heavily affected by some of the large cap companies in the financial sector, particularly DNB and SpareBank 1 SR-Bank, as these companies have high market values, many transactions and very low spreads. However, surprisingly, when regressing the size factor on each sector, we find that size factor has a positive coefficient for financial firms, although the significance is low. For the industrial, oil and shipping and miscellaneous sectors however, the coefficient remains strongly negative and statistically significant at the 1 percent level, indicating a possible size risk premium in these sectors.

While it has been proven empirically that small-cap firms earn abnormal returns, the explanation for why they do so is more controversial (de Groot & Huij, 2018). If we assume that the small-cap premium is due to distress risk, investors should only get compensated for the increased distress probability. De Groot and Huji research this, and conclude that small-cap companies have a significant premium, even after adjusting for the increased default probabilities of smaller companies. Our results are very much in line with the ones of De Groot and Huji, as we find that smaller bonds have significantly higher mispricing than their large-cap counterparts. Our results do however differ from De Groot and Huji, who find that the small-cap premium is most present for low-risk small-cap companies, while our mispricing is greatest in the industrial, oil and shipping sector, consisting of many high-risk companies.

There are several possible reasons for why the risk premium associated with smaller companies exists. de Groot and Huij (2018) argue that smaller companies are more likely to underperform in times of economic downturn, and investors therefore demand a premium for this risk. In fact, they find that the small-cap risk premium is most present during times of economic downturn, indicating that risk averse investors shy away from smaller companies in these times. This can serve as a possible explanation also for our sample, as there have been two major economic downturns over the last decade: the oil crisis in 2015-2016 and the Covid-19 crisis. As the industrial, oil and shipping sector was particularly affected by the first crisis, the small-cap risk premium in this period may serve as a reason for the highest mispricing being in this sector.

Another possible explanation is the low liquidity associated with smaller companies. In fact, when measured together with other variables, the size factor remains much more significant than all of our three liquidity measures, who all have limited significance. It is therefore possible that the size factor in our regression models could include some aspects of a liquidity premium not measured by the liquidity variables.

5.1.3 Liquidity premium

The liquidity premium is widely recognized in existing research as one of the primary explanations for the credit spread puzzle. Investors typically demand a premium for holding illiquid bonds due to potential selling challenges and associated costs. Using market-wide and firm-specific liquidity measures, Longstaff et al. (2005) establish a strong correlation between mispricing and liquidity. Houweling et al. (2005) concur and note that the liquidity component fluctuates significantly over time. Rakkestad et al. (2013) identify that Norwegian corporate bonds are generally illiquid, making it challenging to use standard liquidity measures in the Norwegian market. Sæbø (2011) acknowledges the relevance of market-wide liquidity measures as a risk factor in Norwegian markets. Like other Norwegian studies, Sæbø highlights the challenges in using firm-specific liquidity metrics but proposes that the size factor may partially include compensation for liquidity.

In our analysis, we have applied three distinct liquidity measures, drawing on proxies previously established both internationally and domestically. For market-wide liquidity, we have adopted the price impact measure from Dick-Nielsen et al. (2015) and the Norwegian TED spread, following the approach of Sæbø (2011). For firm-specific liquidity, we use bond size, as Sæbø (2011) suggested. This is based on the premise that investors will demand a risk premium for smaller bonds as these are deemed less liquid.

While our regression results confirm the significance of liquidity measures, our findings differ from international studies like Longstaff et al. (2005), who identify liquidity as the most influential risk premium, second only to default. While our findings show that bond size is insignificant when combined with several other variables, we cannot conclude that firm-specific factors do not affect liquidity premiums. Sæbø (2011) argues that the size factor, measured by market cap, may also encapsulate a liquidity premium demanded by investors for small companies. This hypothesis gains greater credence when examining the regression results over different periods. In the first two periods, when the size factor significantly impacted mispricing, the inclusion of liquidity factors yielded little additional insight. However, in the later period, as the size factor's significance diminished, the impact of liquidity factors became more pronounced. These observations support the hypothesis that part of the significant size premium might be due to liquidity reasons. Perhaps, if we were able to use better issuer-specific liquidity measures, the results would have been different.

It is essential to consider the potential general illiquidity of the Norwegian bond market, which may limit the ability to discern liquidity-based differences in credit spreads. If we assume that all bonds in our sample are illiquid, then liquidity differences between the bonds would not be able to explain liquidity premium differences between a liquid and an illiquid bond. The findings of Rakkestad et al. (2013) and Ødegaard (2017) support the assumption of illiquidity in the Norwegian bond market, highlighting the limited trading activity of most corporate bonds. Furthermore, Rakkestad and Hein (2004) define the Norwegian government bond market as illiquid, making it unsuitable as a risk-free reference rate. Rakkestad et al. (2013) also demonstrate that Norwegian government bonds have significantly higher turnover than corporate bonds. Given this context, it is plausible to characterize the Norwegian corporate bond market as illiquid, strengthening the hypothesis that there is a significant liquidity premium in the market as a whole.

5.1.4 Market Sentiment premium

Cremers et al. (2008) propose that investors in the corporate bond market demand a risk premium towards unexpected, rare events, a factor that contributes to a "jump-risk" premium. Chen (2010) investigates the effects of business cycles on credit spreads and corroborates this risk premium's existence in the market.

While the VIX Index is significant in the univariate analysis, its impact diminishes in the multivariate regression. There are, however, distinct variations across different sectors and time frames. Notably, the financial sector, known for its lower risk profile, has the highest correlation with the VIX Index. Given its low spreads and high investment grade concentration, it likely attracts more risk-averse investors than the other sectors. These investors tend to demand higher premiums in times of high uncertainty, indicated by the VIX Index. Therefore, our results may suggest that higher uncertainty affect the most risk-averse investors the most. In contrast, investors in the industrial, oil and shipping sector, with mostly high-yield companies, appear less affected by fluctuations in the VIX, with investors possibly seeking smaller uncertainty premiums due to their high risk tolerance.

The significance of the VIX Index in our regression analysis becomes particularly notable the last four years, suggesting increased risk aversion over this period. However, it is essential to consider the impact of the COVID-19 crisis, a time when both the VIX Index and the actual spreads rose dramatically, which may have significantly affected these results. Overall, our findings support the theory that risk-averse investors demand an extra premium in periods of high uncertainty, aligning with the results of Cremers et al. (2008).

In our analysis, the oil price emerges as a significant factor with a negative coefficient, combined with sector dummies for Model 7 in Table 4.7. This can strengthen the hypothesis that all parts of the Norwegian economy are affected by the oil price cycles and that investors demand an additional premium when the oil price falls. These findings become less distinct in the sector-specific multivariate regressions. In these analyses, the oil price coefficient retains its statistical significance only for the industrial, oil and shipping sectors, which seems reasonable. This may indicate that when controlling for other variables, oil price movements are more of a sector risk than a business cycle risk.

In conclusion, our analysis suggests the presence of a jump-risk premium in the Norwegian corporate bond market, akin to the concept described by Cremers et al. (2008). Risk-averse investors' heightened response to changes in the VIX Index actively demonstrates this.

Contrary to Chen (2010), we do not find enough evidence to indicate a clear business cycle risk affecting all sectors, at least not measured by the oil price.

5.1.5 The Effect of Leverage

The leverage ratio's impact is widely recognized in the literature as a critical factor in explaining the credit spread puzzle. Eom et al. (2004) observed that structural models often overestimate spreads for high-leverage bonds and underestimate for low-leverage ones. Bai et al. (2020) support this view and argue that the Credit Spread Puzzle is only present in the safest rating categories. Conversely, Feldhütter and Schaefer (2018), disagree and find that the Credit Spread Puzzle is present only for high-yield bonds. The ongoing debate demonstrates the complexity of understanding the leverage ratio's influence on credit spreads.

In our regression results, the influence of the leverage ratio shows variability. The univariable regression yields a negative coefficient, suggesting that a higher leverage ratio correlates with lower absolute mispricing. However, in the multivariable regressions, the coefficients become significantly positive, consistent across all periods. Intriguingly, while the positive relationship holds for the two non-financial sectors, it reverses to a significantly negative coefficient for the financial sector, highlighting sector-specific dynamics in the leverage ratio's impact.

A plausible explanation is that high leverage in the riskier non-financial sectors increases vulnerability to business cycles and economic downturns. Highly levered firms in these sectors involve great risk, potentially deterring investors with low or average risk tolerance, contributing to mispricing. Conversely, higher leverages correlate negatively with mispricing in the relatively safer financial category, suggesting that investors do not seek additional risk premium investing in the highest levered of these more secure companies.

However, caution is advised interpreting these results too directly. Firstly, with regards to leverage, financial firms' capital structure differs significantly from other sectors, making cross-sector comparison difficult. Secondly, the industrial, oil and shipping sector includes many near-bankrupt observations from 2015-16, where negligible equity values led to leverage ratios of almost 100 percent. The actual spreads on these observations are also the highest in our sample, so their inclusion could significantly skew the results.

Our findings suggest that investors in the industrial, oil and shipping and miscellaneous sectors demand a higher risk premium for high-levered firms, supporting the findings of Feldhütter and Schaefer (2018). However, these results should be interpreted with consideration due to the possible influence of significant outliers. Exploring leverage effects across different rating categories would be a valuable next step when this is possible in the Norwegian market.

5.2 Vulnerability to changes in main input variables

In this section, we investigate the robustness of our model by observing changes in our main variables from the actual and model spread in Equation 2.5 and 2.3. First, we look into the choice of risk-free rate. Then, we will look at changes in the recovery rates assigned to the sectors.

5.2.1 Choice of risk-free rate

In determining the credit spread, we used the swap rate minus ten basis points as our risk-free rate, following the market conventions outlined by Hull et al. (2004) and Sæbø (2015). This choice was made due to instability and low liquidity in Norwegian government bonds, as noted by Rakkestad and Hein (2004).

However, to account for international financial theory viewing government yields as the true risk-free asset, we compare our findings using the swap rate as a risk-free rate to those using government yields. Figure 5.1 visually shows the relationship between each of these rates and the monthly spread.

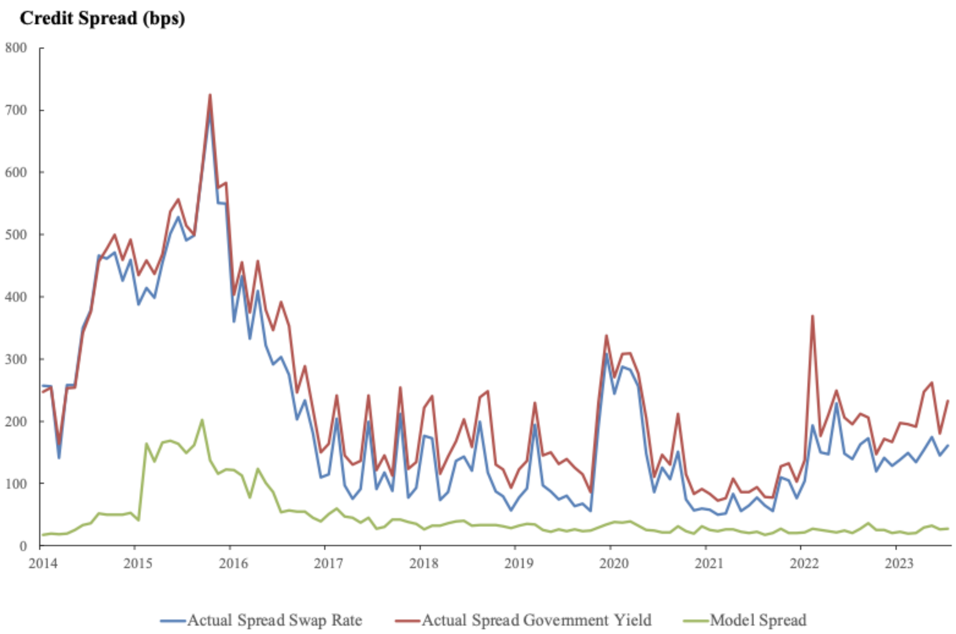

Figure 5.1: Credit spreads with risk-free rate change

The graph reveals that spreads based on the government yield lie consistently higher than those using the swap rate. However, this disparity does not appear large enough to significantly alter our overall conclusions, indicating that using the government yield as a risk-free rate would not materially have impacted our findings.

Table 5.1: Median explained share by sector

	Financial	Industrial, Oil & Shipping	Miscellaneous
Swap as risk-free (%)	51	17	19
Government as risk-free (%)	30	15	16

Table 5.1 presents the median explained share calculated using both risk-free rates. As anticipated, the impact on the industrial, oil and shipping, and miscellaneous sectors is minimal due to their spreads being less sensitive in relative terms. Conversely, the financial sector exhibits significant sensitivity to variations in the risk-free rate. This indicates that the selection of a risk-free rate matters to some degree, particularly when analyzing the credit spread puzzle in relative terms.

5.2.2 Recovery rate

To evaluate the robustness of our conclusions against varying recovery rates, we compare results in the industrial, oil and shipping sector using both the 48 percent recovery rate

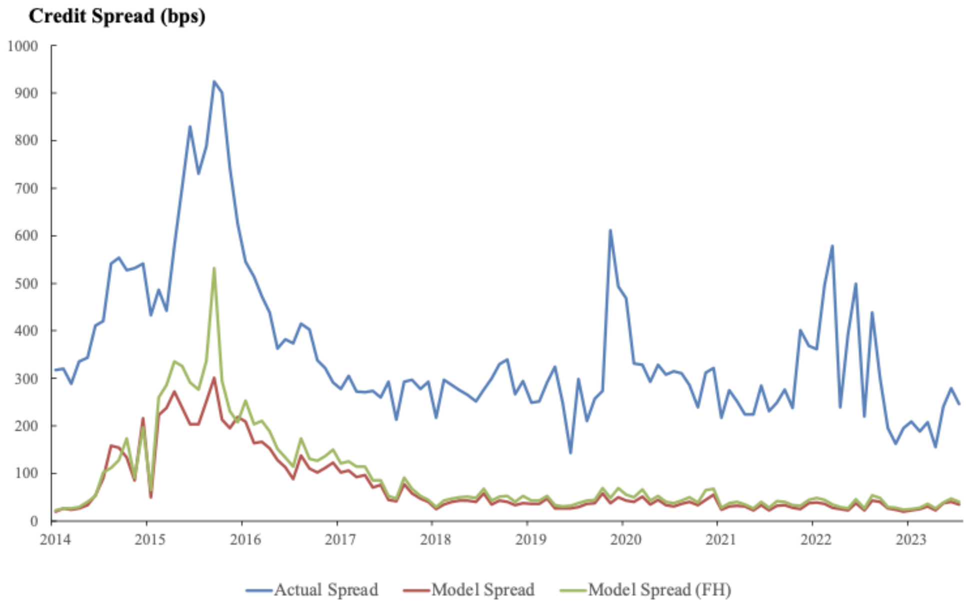

Figure 5.2: Credit spreads with recovery rate change

from Altman and Kuehne (2012) and the recovery rate of 37.8 percent from Feldhütter and Schaefer (2014). This comparison helps us asses the impact of differing recovery rate assumptions on our findings.

The comparison in Figure 5.2 reveals that a lower recovery rate significantly impacts our results in periods of high spreads and default probabilities, such as during the oil crisis in 2015-2016. However, in the subsequent years, its effect diminishes. In all, considering the entire period, slight variations in recovery rates would likely not have significantly altered the primary conclusions of our analysis.

While our analysis uses sector-wide recovery rates, there is a valid argument that adopting issuer-specific recovery rates would have been the ideal strategy. Variances in recoveries, particularly in our diverse miscellaneous sector, suggest that a more dynamic approach to recovery rates could have enhanced model precision. Thus, our conclusion about the presence of the credit spread puzzle in the Norwegian market could partly stem from the fact that investors have different perceptions of issuer-specific recovery rates that our model does not capture.

5.3 Issuer-specific characteristics

While our regression models identify various factors contributing to the credit spread puzzle, a large fraction still remains unaccounted for. As discussed, a significant component could be a market-wide illiquidity perception of the Norwegian corporate bond market, which our liquidity measures do not capture. However, there is also reason to believe that investors consider several issuer-specific variables that our model cannot explain.

First, as previously explained, investors may use dynamic recovery rates, unlike ours, which are static within each sector. Additionally, perceptions of management quality and corporate governance play a role in pricing, given their influence on future performance and risk. Moreover, the intricacies of a firm's capital structure and financing strategies, including the extent and nature of bond covenants, can affect the premium investors demand. These covenants, which can significantly restrict management actions, are not accounted for in the Merton (1974) Model.

We believe that issuer-specific characteristics not captured by the Merton (1974) Model contribute to the extent of the credit spread puzzle in the Norwegian market.

5.4 Recommendations for future research

Before concluding this thesis, we identify several areas for future exploration. Firstly, investigating the effects of different bond types beyond senior unsecured bonds could provide further insights into the puzzle. Moreover, considering the captivating results from altering the risk-free rate, a deeper analysis of its role is also warranted. Further, with an increasing number of Norwegian bonds receiving credit ratings, future studies could incorporate these into their analysis. Specifically, we see potential in studying how leverage impacts the credit spread puzzle across various credit ratings. Finally, our most intriguing recommendation emerges from our discussion on a potential market-wide liquidity premium in Norwegian corporate bonds. Conducting a comparative, cross-border study focusing on liquidity variations could offer valuable insights into the role of liquidity in the Norwegian credit spread puzzle. To conclude, exploring these areas in future research could significantly enhance our understanding of the credit spread puzzle within Norwegian bond markets.

6 Conclusion

Financial research comparing observed credit spreads with those predicted from structural credit models consistently reveal a mismatch, highlighting the phenomenon known as the credit spread puzzle.

Sæbø (2015) introduced the topic to the Norwegian corporate bond market, aiming to assess the extent of the credit spread puzzle. Analyzing data from 2008 and 2013, Sæbø found that, on average, only 28 percent of actual spreads were accounted for by model-derived credit spreads. Since Sæbø's study, there has been limited research on the credit spread puzzle in Norwegian markets. To understand the puzzle's current magnitude in Norway, we analyze a sample of 30,647 transactions between 2014 and 2023, shedding new light on this phenomenon in the Norwegian context.

Our thesis has three primary objectives. First, to quantify the extent of the credit spread puzzle in the Norwegian market over the past decade. Second, if the puzzle does exist, identify the additional risk premiums investors demand in the Norwegian fixed-income market, which cause actual spreads to diverge from model-implied spreads default spreads. Third, to explore the reasons behind investors demanding these additional premiums, should they exist.

Firstly, from 2014 to 2023, the median proportion of actual spreads explained by our default model is 28 percent, in the same region as Sæbø (2015) findings. This figure has remained relatively stable over time, peaking at 32 percent between 2017 and 2019, then dropping to 25 percent after the turn of the decade. Sector-wise, financial firms show a higher explained share (51 percent) than our industrial, oil and shipping (17 percent) and miscellaneous (19 percent) categories. Regarding absolute mispricing, the industrial, oil and shipping sector, specific to the Norwegian market, has the highest mispricing, with a median of 264 basis points over the entire period.

Having confirmed the presence of the credit spread puzzle in the Norwegian corporate bond market, we next explore the additional risk premium, beyond default risk, that Norwegian bond investors require as compensation. From previous literature on the topic, we identify various risk measures for this purpose.

Our results indicate that Norwegian investors seek additional compensation when investing in specific sectors and bonds of small issuers, supporting previous literature. In particular, the industrial, oil, and shipping sector shows the highest mispricing, indicating that investors are likely to demand an additional sector premium, especially compared to the financial sector. We attribute this sector premium to cyclicality, the impact of the oil crisis in 2015-2016 and aversion towards high-yield bonds.

The size premium is particularly pronounced in the Norwegian market, with smaller companies consistently having higher spreads, especially in sectors prone to economic downturns.

Quantifying the liquidity premium demanded by investors poses a challenge, as assessing liquidity in the Norwegian market is difficult due to low trading volume and over-the-counter trading. However, we suspect that components of the significant size premium observed are attributable to liquidity considerations.

While we have identified potential risk premiums, a significant portion of mispricing between actual and model spreads remains unaccounted for. We attribute this to two potential reasons. Firstly, the generally illiquid nature of the market suggests a substantial liquidity premium, which our and previous studies struggle to quantify. Secondly, we suspect considerable issuer-specific components not fully captured by the Merton (1974) Model, suggesting that bond pricing in the actual market is more nuanced and complex than what can be explained by a model with a few key inputs.

7 Appendix

A Assumptions of the POLS Model

The Pooled Ordinary Least Squares (POLS) model is a linear regression model commonly used in panel data analysis. According to **Wooldridge (2019)**, the assumptions underlying the POLS model, which are similar to those for ordinary least squares (OLS) regression adapted to panel data, include:

1. **Linearity**: The relationship between the independent variables and the dependent variable is linear.
2. **Independence**: Observations are independent across time and entities.
3. **No perfect multicollinearity**: The independent variables are not perfectly correlated with each other.
4. **Zero conditional mean**: The expected value of the error term, conditional on the independent variables, is zero.
5. **Homoscedasticity**: The error term has a constant variance (no heteroscedasticity).
6. **No autocorrelation**: There is no correlation in the errors over time for any given cross-sectional unit.

B Autocorrelation and Heteroscedasticity

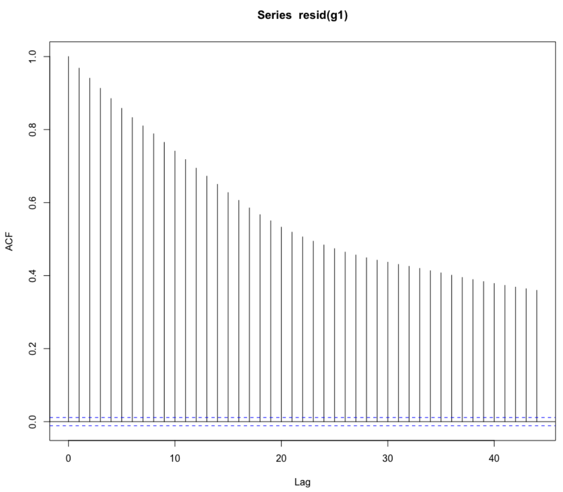

Figure B.1: ACF Plot

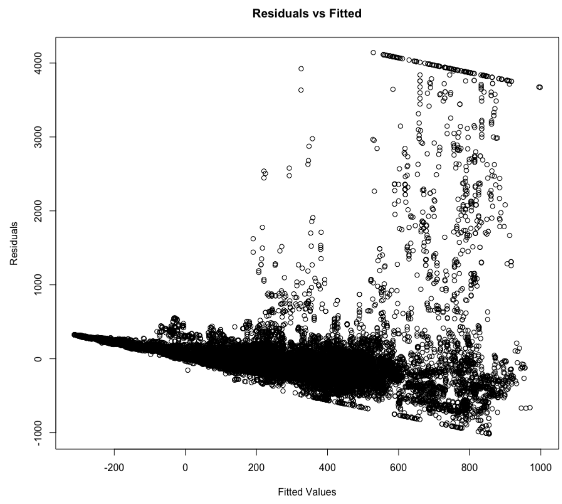

Figure B.2: Residual Plot

C Multicollinearity and Correlation Matrix

Variable	VIF	1/VIF
Industrial, Oil & Shipping	3.33	0.30
Miscellaneous	2.53	0.39
log(Market Cap)	1.42	0.70
Leverage Ratio	2.51	0.40
Price Impact	1.25	0.80
TED spread	1.04	0.96
log(Bond Size)	1.14	0.88
Time-to-Maturity	1.05	0.95
VIX Index	1.12	0.89
Oil Price	1.19	0.84

Multicollinearity indication: $VIF > 5$, $1/VIF = 0$.

Table C.1: Variance Inflation Factor (VIF) Test Results

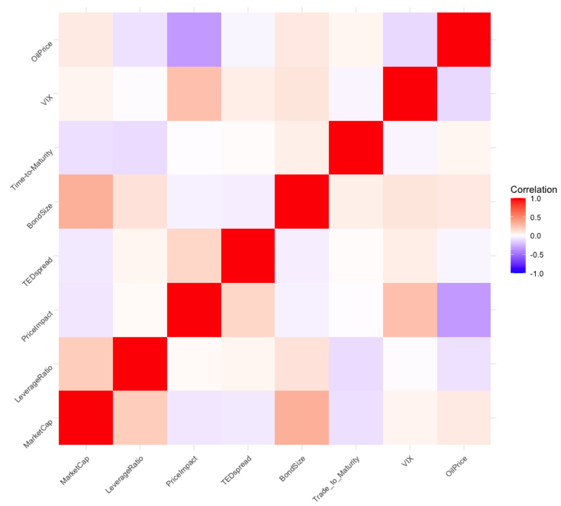

Figure C.1: Correlation Matrix

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