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Estimating the Liquidity Premium in the Norwegian High Yield Bond Market

An Empirical Analysis of the Norwegian High Yield Bond Market and Its Liquidity Premium in the Period 2009 - 2021

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Executive Summary

We estimate the liquidity in the Norwegian High Yield Bond Market (Norwegian HY) using transaction data from January 01, 2009, to October 05, 2021. We aim to quantify how much investors, on average, require as compensation for the Norwegian HY being illiquid. Hence, our main contribution is estimating the average liquidity premium as a share of the yield spread. The study we carry out starts with estimating liquidity in Norwegian HY with three transaction cost estimators, two price dispersion measures, and one price impact measure. Then, we analyze and compare the liquidity measures descriptively and empirically. Finally, we conduct an empirical correlation study on the yield spread and the liquidity measures to examine how much of the variation in the yield spread that can be explained by illiquidity.

We find significant correlations for the liquidity measures with bond characteristics and trading activity variables. This indicates that the relevant variables, on average, can say something about a bond's liquidity. On the other hand, we also find that the various liquidity measures deviate markedly in their estimates, implying that approximating liquidity in Norwegian HY is a challenging task. Nonetheless, we observe a significant relationship between less liquid bonds and higher yield spreads for four out of six measures. These four measures also describe relatively equal proportions of the yield spread. That is between 20.5% and 26.9%. Thus, we estimate the average size of the liquidity premium in Norwegian HY to be within this interval. These results show that investors in Norwegian HY require a considerable premium for the market's illiquidity.

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1. Introduction

1.1 The Scope of the Thesis

The topic for this thesis is based on a common thought of the Norwegian High Yield Bond Market (Norwegian HY) being illiquid. We aim to investigate the extent to which this is the case and the role liquidity concerns play in the pricing of the bonds. There exists solid research on liquidity-related topics among other Over-the-Counter markets, especially in the U.S. However, there is modest research on similar issues in Norwegian markets. That is the motivation behind the topic of our thesis, which aims to analyze liquidity effects in Norwegian HY and quantify the liquidity premium.

The liquidity premium is the compensation investors require due to the illiquidity of a security and is universally accepted as a part of the yield spread. However, very few attempts in quantifying its size have been carried out for Norwegian HY. To conduct such an analysis, we start by measuring liquidity. Then, we run various regressions based on the liquidity measures with two main intentions. First, to find variables that correlate with liquidity. Second, to estimate how much variation in the yield spread that can be explained by the various liquidity measures. Based on this, we aim to provide an estimate of the size of the average liquidity premium in Norwegian HY.

1.2 The Norwegian High Yield Bond Market

In this section, we present a brief description of the structure and characteristics of Norwegian HY. The market involves corporate bonds with a Norwegian International Security Identification Number (ISIN) with a lower credit rating than Investment Grade (IG) bonds. Usually, a high yield bond is defined as a bond assigned credit rating BB+ or lower by one of the three big credit rating agencies (Moody's, S&P, or Fitch).[1] However, few Norwegian bonds have an official credit rating. We rely on Nordic Trustee and Stamdata in distinguishing between HY and IG for the Norwegian bond market.

[1] BB+ using S&P's and Fitch's scale. The equivalent for Moody's is Ba1.

The bond market is separated into the primary and secondary markets. The primary market is for the issuance of corporate bonds. A company issue a bond to raise capital and the debt is sold to an investor. This is a market of high concentration in Norway. The demand side is dominated by a few major institutional investors. On the supply side, there are 562 companies that have at least one outstanding bond as of 1. January 2021.[2] Of the issued amount from 2010 to 2021, the three largest managers (Pareto Securities, Nordea, and DNB, respectively) accounted for about 36% of the total amount (Nordic Trustee, 2021).

The size of the market has increased substantially over the last two decades. Figures from Nordic Trustee (2021) present that the market has grown from around 10 billion NOK in total outstanding amount at the turn of the millennium to about 140 billion NOK a decade later. In 2021, the figure was approximately 289 billion NOK. As a comparison, the current combined Swedish, Danish and Finnish HY market is about 199 billion NOK. Norwegian HY is dominated by floating-rate notes, where coupon payments are dependent on a reference rate (typically 3-Month NIBOR). The typical repayment structure is bullet, where the entire principal is repaid on the bond's maturity date. We will elaborate more on the structure of the bonds in Norwegian HY in section 3.2.

The secondary market is where bonds are bought and sold between investors. In the secondary market, the transaction is just a mere change of who owns the bond, and the transaction does not raise any additional capital for the issuer. In our analysis, we solely focus on the secondary market. This market is organized as an Over-the-Counter (OTC) market, meaning the bonds are traded directly between buyer and seller and not at a central marketplace. Most trades go through an intermediary, usually an investment bank. The OTC format has affected the transparency of the Norwegian HY. Historically, a considerable number of trades have not been reported. However, the transparency has improved, and most trades are now reported through Euronext Oslo.

[2] Based on data provided by Stamdata. To be elaborated in section 3.1.2.

2. Literature Review

We aim to establish an overview of the most relevant literature in shaping the topic of this thesis. We first present literature on Norwegian HY before focusing more generally on liquidity in OTC markets and studies on the relationship between liquidity and the yield spread.

There is not much research conducted on liquidity in Norwegian HY. Sæbø (2015) explores the credit spread, but he puts a stronger emphasis on the expected loss component of the credit spread and less focus on liquidity. He finds that about 46% of the credit spread in Norwegian HY is due to investors requiring compensation for the expected loss, leaving the remaining 54% for other factors. Sæbø (2015) suggests liquidity to be one of the factors that might explain the part of the spread that is not explained by expected loss.[3] As far as we recognize, a comprehensive study addressing how liquidity affects the pricing of Norwegian HY bonds is a relatively unexplored topic in the academic literature.

There exists extensive research on the effect of liquidity on asset prices in other OTC markets. Friewald et al. (2017) measure liquidity in the U.S. Structured Product Market, which involves securities more complex in structure compared to the Norwegian HY bonds that we aim to analyze. However, as with Norwegian HY, the trading frequency is relatively low. They find that liquidity is a significant factor in explaining the yield spread. Dick-Nielsen et al. (2012) and Friewald et al. (2012) analyze whether liquidity is an important price factor in the U.S. Corporate Bond Market. Both conclude that liquidity is a significant price factor, and the latter find that it is significantly higher for HY bonds than for IG.[4]

Friewald et al. (2017) also study how the level of detail of the transaction data is related to the accuracy of the various liquidity measures. They find that, in general, liquidity measures that use dealer-specific information can be efficiently proxied by measures that use less detailed information. This is valuable for this thesis as we do not hold dealer-specific information. Another liquidity horse race is the study by Schestag et al. (2016), which compares numerous high and low-frequency liquidity measures on the U.S. Corporate Bond Market. Based on both

[3] Elton et al. (2001) and Collin-Dufresne et al. (2001) suggest liquidity as a possible explanation for the unexplained part of the credit spread in the U.S. corporate bond market.

[4] See also Amihud et al. (2005) for a comprehensive study on how liquidity affect asset prices.

Friewald et al. (2017) and Schestag et al. (2016), we have selected the liquidity measures most suitable given the granularity of the data we possess for Norwegian HY.

The topic of our thesis is formed as we, based on the literature highlighted above, observe a lack of research on quantifying the liquidity premium in the Norwegian HY market. In this thesis we aim to narrow this gap by establishing a diverse set of liquidity measures to quantify how much investors of the Norwegian HY market require as compensation for its illiquidity.

3. Data

We employ three different data categories. That is, transaction data, bond characteristics data, and theoretical pricing data. The former comprises transactions in the secondary market for bonds with Norwegian ISIN from January 01, 2009, to October 05, 2021, listed on either Oslo Stock Exchange (OSE) or the Alternative Bond Market (ABM).

3.1 Data Sources

3.1.1 Transaction Data – Pareto Securities

Pareto Securities has provided us with their database of transactions for listed bonds with Norwegian ISIN on either OSE or ABM. If every transaction within both these markets were reported to Euronext, we would possess a complete set of transactions. However, this is probably not the case. The various investment banks conducting trades usually hold different reporting routines. Moreover, since the beginning of 2009, reporting routines can have changed internally within those organizations. Consequently, the transaction data we base our analysis on is somewhat unbalanced and, thus, does not fully represent the secondary market. Nonetheless, this is probably the best starting point we can expect to obtain for what we intend to study. Each transaction holds information on *Price, Ticker, Date, Volume,* and *Maturity,* which we use in our analysis.

3.1.2 Bond Characteristics Data – Nordic Trustee

Nordic Trustee has given us temporary access to Stamdata, which is an exhaustive platform with market information on Nordic fixed income. Based on information on *Ticker* from the transaction data, we use bond characteristic data from Stamdata to obtain more information on the bond traded in each transaction. The information from Stamdata is valuable for aggregation purposes, e.g., by industry sector or currency. Furthermore, we use Stamdata's issue risk classification (HY/IG) to categorize which of the two segments each transaction belongs to. We also use information on types of issue, redemption, and risk to filter the transaction data before the analysis (to be elaborated in section 3.2). Additionally, we use the bond characteristics *ISIN, Outstanding Amount, Coupon Rate*, *Coupon Type, Country*, *Bond Market* (OSE or ABM), *Currency*, and *Sector* from Stamdata.

3.1.3 Theoretical Pricing Data – Nordic Bond Pricing

Nordic Bond Pricing (NBP) has provided us with daily, theoretical pricing since mid-2014 for bonds within Norwegian HY's five largest sectors: Oil and Gas Services, Oil and Gas E&P, Shipping, Transportation, and Industry. This includes theoretical bid, ask, and mid quotes for each day, which are used in the computation of one of the liquidity measures.

3.2 Data Processing

The initial data obtained from Pareto merged with information from Stamdata comprise 81,417 HY transactions. Before establishing any liquidity measures, we conduct some data processing operations to obtain better comparability among the included transactions. We only include senior unsecured bonds and leave different types of optionality behind (e.g., call, put, cap, and floor). Tables 1 and 2 illustrate that after filtering on risk and issue type, we reduce the number of transactions to 58,137.

Table 1 – Risk Type

Risk	Transactions	Proportion [%]
Senior Unsecured	59,099	72.59
Senior Secured	14,364	17.64
Other	7,954	9.77
Total	81,417	100.00

Table 1 - Filtering based on risk type.

We have the following based on the remaining 59,099 transactions of senior unsecured debt.

Table 2 – Issue Type

Issue Type	Transactions	Proportion [%]
Bond	58,137	98.37
Claim, Redemption	516	0.87
Convertible	403	0.68
Certificate of Deposit	43	0.07
Total	59,099	100.00

Table 2 - Filtering based on issue type.

The next step to improve comparability is to solely consider bonds with the same repayment structure. Thus, we leave out all redemption types that are not structured as bullet, as displayed in Table 3.

Table 3 – Redemption Type		
Redemption Type	**Transactions**	**Proportion** [%]
Bullet	56,186	96.64
Irregular	1,941	3.34
Serial	10	0.02
Total	58,137	100.00

Table 3 - Filtering based on redemption type.

Next, we leave out transactions for bonds that have less than half a year to maturity, which removes another 2,765 transactions. The yield spread for bonds with a short time to maturity is usually affected by other factors than those with a longer time to maturity. Hence, including bonds with less than half a year to maturity may create unnecessary noise in the regressions presented in section 5.2.

The next part of data processing is about reducing the effect of 'fake' outliers, i.e., outliers caused by data entry errors. For instance, 15. November 2012, SELV03 PRO (Selvaag Gruppen) was traded twice. First with a price of 101.625 and then a thousand times higher at 101,625. This is obviously an entry error and thus a fake outlier we would like to avoid. We utilize the price-median filter introduced by Edwards et al. (2007). For each bond, we eliminate transactions that deviate with more than 20% from the median transaction within nine trading days, centered on the transaction date. This operation removes another 27 transactions leaving us with 53,394.

For all bonds trading by a foreign currency, which corresponds to about 16% of all transactions, we transform the variables *Volume* and *Outstanding Amount* to Norwegian Kroner (NOK) based on daily exchange rates for the entire time series. We also winsorize the data on *Volume,* where all transactions with values above the 99.9 percentile and below the 0.1 percentile are set to the corresponding percentile's value.

3.3 Additional Variables

We have included two variables in addition to what we have obtained from the sources described above. That is *Yield Spread* and *Credit Rating*. The yield spread is defined as the difference between the yield to maturity of a bond and the 3-month NIBOR rate. We have calculated the yield spread Y_{it} for all floating rate and fixed rate bonds based on their coupon rate C_i, the daily 3-month NIBOR rate N_t, price P_{it}, face value F_i, and years to maturity TTM_{it}. $\mathbb{F}_i = 1$ if bond i has a floating rate, else $\mathbb{F}_i = 0$ if bond i has a fixed rate. Other coupon rate types are excluded from the calculations reflected in equation 1.[5]

$$Y_{it} = \frac{(C_i + \mathbb{F}_i N_t) + \frac{F_i - P_{it}}{TTM_{it}}}{\frac{F_i + P_{it}}{2}} - N_t \tag{1}$$

We also hold yield spreads for each transaction extracted from Bloomberg, distributed to us from Pareto Securities based on their transaction data. Predominantly, we use our own yield spread, which is very similar to Bloomberg's. However, for all bonds with other coupon types, we use Bloomberg's yield spread. This is also used if our yield spread turns negative.[6] In the rare scenario where both Bloomberg's and our yield spread is negative, we set it to zero as a negative yield spread in Norwegian HY seems unreasonable.[7] The results we present in the upcoming empirical analysis in section 5.2 remain, practically, unchanged when changing between ours and Bloomberg's yield spreads.

Regarding the second variable, very few Norwegian issuers have an accessible credit rating from, for instance, Moody's, S&P or Fitch. A credit rating variable is central in the regressions in our upcoming analysis to capture variations driven by a company's probability of default, which is an essential component of the yield spread. Therefore, we have created a similar ordinal variable ranging from A to F. FundingPartner AS has provided us with access to their credit model, which predicts the probability of default for Norwegian companies. Based on the

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[5] Note that this formula is an approximation for the yield to maturity where the 3-month NIBOR is subtracted.

[6] 9 occurrences of negative yield to maturity and 72 occurrences of negative yield spread. The former could happen if, for instance, there has been a restructuring of a bond *after* a given transaction with a specified price found place. If this bond previously traded with a higher coupon rate than the current C_i (which we employ across the entire time series) the yield to maturity could turn negative.

[7] 3 occurrences.

numerical output from the model, we have created an ordinal credit variable.[8] Some issuers have been reranked depending on a qualitative evaluation, and companies from other countries have been placed in rankings depending on their Norwegian peers. Of course, this is not a perfect substitute for a comprehensive rating from a credit rating agency, but a proxy we believe is valuable to distinguish some variations following an issuer's probability of default.

3.4 Descriptive Statistics

In this section, we provide a brief overview by presenting descriptive statistics of the transaction data to be used for our liquidity analysis. The statistics are obtained after the data processing. First, we present relevant numerical variables for all transactions in Table 4.

Table 4 - Descriptive Statistics for Numerical variables

Variable	Mean	Standard Deviation	Median	5th percentile	95th percentile
Outstanding Amount (M.NOK)	1,099.86	811.52	900.00	300.00	2,145.00
Volume (M.NOK)	6.49	21.49	2.50	0.50	22.00
Time to Maturity (y)	2.98	1.56	2.92	0.84	5.14
Age (y)	2.34	2.19	1.93	0.35	5.10
Coupon Rate (%)	5.40	2.26	4.75	2.85	9.75
Spread (%)	7.00	12.10	4.50	1.91	16.66

Table 4 - Descriptive statistics for numerical values in the transaction data. Volume and Outstanding Amount are denoted in millions of NOK.

[8] Probability of default classification *before* the manual evaluation in percentages: A: [0,1); B: [1,2); C: [2,4); D: [4,8); E: [8,16); F: [16,100).

The standard deviation of the *Spread* is 12.10%, which seems high compared to the mean. However, the spread variable has some extreme right-tail observations, which are essential in increasing the standard deviation. For instance, the maximum value is 303.88%. The average *Outstanding Amount* and *Volume* corresponds to 1,099,860,000 NOK and 6,488,260 NOK, respectively. The average *Time to Maturity* is 2.98 years. Furthermore, the average *Age* of a bond when traded is 2.34 years, and the average *Coupon Rate* is 5.40%. We observe that the distribution of all numerical variables is somewhat right-skewed.

Next, we summarize some central categorical variables displayed in Tables 5 and 6. The former table shows that Shipping is the most frequently traded *Sector* and encompasses the highest number of traded bonds. We also observe that Norwegian companies are most frequently traded based on transactions, bonds, and issuers. The latter table exhibits that 15.83% of the transactions were conducted in a currency other than NOK. Moreover, most of the transactions have been carried out on bonds listed on OSE, and bonds with a floating rate note are most traded. We also observe that 2013 to 2016 was the period most trades took place during this time series.

Table 5 – Descriptive Statistics for Categorical Variables				
	Transactions	**Proportion** [%]	**Bonds**	**Issuers**
Sectors				
Shipping	14,451	27.06	98	25
Oil and Gas Services	13,743	25.74	74	29
Industry	10,415	19.51	55	14
Transportation	4,628	8.67	25	9
Oil and Gas E&P	4,008	7.51	31	16
Other	6,131	11.51	57	27
Country				
Norway	34,132	63.92	238	75
BCCFLM[9]	14,741	27.61	69	23
Other Scandinavia	1,692	3.17	15	7
United Kingdom	1,307	2.45	6	5
USA	258	0.48	2	1
Other	1,264	2.37	10	9
Credit Rating				
A	3,440	6.44	31	9
B	14,008	26.24	100	36
C	19,535	36.59	100	28
D	9,770	18.30	54	26
E	3,584	6.71	32	14
F	3,057	5.73	23	7
Total	53,394	100.00	340	120

Table 5 – Descriptive statistics on industries, countries, and credit rating.

[9] Bermuda, Cayman Islands, Cyprus, Faroe Islands, Luxembourg, Marshall Islands.

Table 6 – Descriptive Statistics for Other Categorical Variables		
	Transactions	**Proportion** [%]
Currency		
NOK	44,938	84.16
USD	5,641	10.56
EUR	1,625	3.04
SEK	1,190	2.23
Coupon Type		
Floating Rate Note	44,280	82.93
Fixed Rate	7,257	13.59
Step Rate	974	1.82
Adjustable Rate	653	1.22
Zero Coupon Bond	230	0.43
Stock Exchange		
OSE	44,382	83.12
ABM	9,012	16.88
Year		
2009 - 2010	1,833	3.43
2011 - 2012	7,008	13.12
2013 - 2014	14,577	27.30
2015 - 2016	11,186	20.95
2017 - 2018	8,581	16.07
2019 - 2020	7,581	14.20
2021 (05.10)	2,628	4.92
Total	53,394	100

Table 6 - Descriptive statistics for currency, coupon type, stock exchange, and year.

4. Liquidity Measures

4.1 What Does Liquidity in a Secondary Market Involve?

We start this chapter by providing a high-level explanation of what liquidity in a secondary market involves. A security is considered liquid if a transaction can be carried out relatively quickly and with a low transaction cost. If a portfolio manager can close a position fast without leaving a considerable discount to the fair value, we say that the underlying security is liquid. Usually, liquid markets are characterized by several sellers and buyers for high-demand and standardized products. For instance, the Apple stock is a liquid security as one can sell it immediately and relatively close to what the market considers to be the fair value at the given time. Thus, the key characteristic of a liquid market is that there always exist market participants willing to buy and sell a security close to the fundamental value.

Estimating the transaction cost is a common way to quantify liquidity as it involves the cost of executing a transaction in a market. Exploiting the difference between the ask and bid price is often used for this purpose as it says something about what a financial instrument can be both sold and bought for in a given moment. In our Apple example above, this difference is practically zero. There are many ways to measure liquidity, and in the following sections we elaborate on a selection of liquidity measures that we believe suits Norwegian HY.

Before introducing the liquidity measures, we find it important to emphasize findings made by Mahanti et al. (2008) on latent liquidity, which we believe is central in Norwegian HY. Trading activity in a market is a symptom of liquidity as markets for financial instruments with few trades tend to be illiquid. However, low trading activity does not necessarily mean that a security is illiquid. Despite a bond not being traded, it might be relatively liquid depending on the investors holding the specific bond.

We argue that awareness of latent liquidity is essential in Norwegian HY. The market participants are dominated by relatively few institutional investors. Various investor characteristics provide large variations in the average holding time of a bond. For instance, there are high turnover investors such as hedge funds on one side and low turnover institutions such as pension funds on the other. If a given bond is mainly held by high-turnover hedge funds, it should be considered relatively liquid despite not being heavily traded. This is because the bond is relatively easily accessible. Consequently, liquidity can also be measured as a function of the investors holding a bond without considering the specific bond's transaction activity, as Mahanti et al. (2008) describe. This idea is important to bear in mind as the liquidity measures we present cannot account for latent liquidity. This will be elaborated in section 7.1 as a suggestion for further research.

4.2 Introduction to the Liquidity Measures

This section describes the liquidity measures we employ for our upcoming analysis. The availability of data somewhat limits the measures that can be applied. Measures that require bid-ask quotes, such as the bid-ask spread, or individual dealer-specific information, such as the round-trip cost, are not possible to compute with our data. However, we can compute other measures that merely require information on price and volume. There is no consensus in the literature on how to precisely measure the liquidity of an asset based on the data we possess. Friewald et al. (2017) and Schestag et al. (2016) explore and evaluate a wide variety of liquidity measures for OTC markets. That is, the U.S. Structured Product Market and the U.S. Corporate Bond Market, respectively. The former publication finds evidence that, in general, liquidity measures using more detailed data, such as the round-trip cost, can be satisfactorily proxied for by measures that require less data. Based on both these publications, we explore a set of different measures attempting to proxy the liquidity cost for the Norwegian HY market.

All liquidity measures we utilize take either price, volume, or both into account. We have picked three measures that estimate the transaction cost. That is, the imputed round-trip cost, the Roll measure, and Corwin and Schultz's high-low spread estimator. Additionally, we calculate a price impact measure, namely the Amihud measure. We also compute two versions of the price dispersion measure. Based on these six measures, we will conduct analyses on quantifying the liquidity in Norwegian HY. In the following, we will describe the fundamentals of each of the measures and elaborate on essential assumptions and adjustments in the calculations.

4.3 The Imputed Round-Trip Cost

4.3.1 Calculation of the Measure

The imputed round-trip cost (IRT) was presented by Feldhütter (2012) and applied by Dick-Nielsen et al. (2012).[10] The measure approximates the round-trip cost and uses observed prices to estimate this. A round-trip cost is defined as the difference between the price at which a dealer sells a bond to a customer and the price at which the dealer buys the same bond from another customer. Thus, the round-trip cost is assumed to be the bid-ask spread. The idea is that if a bond that has not traded for a while suddenly trades two, or three times at the same volume within a relatively short period, it seems likely that this is a round-trip trade. By locating these trades, we can compute the imputed round-trip cost and find an estimate of the transaction cost. The formula of the measure is presented in Appendix 8.1.1.

4.3.2 Adjustments

Friewald et al. (2017) find that the IRT is a well-performing proxy to the more comprehensive round-trip cost measure. In their calculations, the trades must happen within 15 minutes to be evaluated as a round-trip trade. In addition, the trades must have the exact same volume. In our calculations, we also require identical volumes between the trades. However, we relax the time constraint from 15 minutes to intraday. The main reason for this is that our data include the date of the trade in chronological order but lacks the exact time in which the trade found place. Euronext operates by the principle of deferred publication, meaning that trades are reported continuously but only go public after closing time. Furthermore, as most of the bonds in Norwegian HY trade relatively infrequent, the time between some round-trip trades may be on a considerably rarer basis than 15 minutes, possibly several days. However, robustness checks conducted by Friewald et al. (2017) reveal that increasing the round-trip period to, for instance, one week only marginally affects the liquidity measure's magnitude. Further, they state that there exists empirical evidence showing that a large fraction of round-trip trades happen within a single day. Consequently, we find an intraday period satisfactory for this measure.

[10] Feldhütter is one of the authors in Dick-Nielsen et al. (2012) and refer to Feldhütter (2012) when this publication was in press.

Based on the volume and time requirement, we define two consecutive transactions for a given bond a round-trip pair. If an odd number of daily trades satisfy the requirements, the last three transactions go into the same and final 'pair'. Most pairs are constructed based on only two equal transactions within a day, as summarized in Table 7.

Table 7 – Imputed Round-Trip Pairs

Qualified trades intraday	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**11**	**12**	**13**
Occurrences	6,162	547	201	41	17	5	2	1	1	1

Table 7 – Top row: Number of transactions with matching ticker, date, and volume. Bottom row: Occurrences. For example, there are 201 occurrences of 4 transactions with equal ticker, date, and volume yielding a total of $201 * 4 = 804$ transactions. An occurrence of 4 gives 2 round-trips of 2 transactions. An occurrence of 7 gives 2 round-trips of 2 transactions and 1 round-trip of 3 transactions.

This leaves us with 15,163 transactions from the starting point of 53,394, in which we compute the IRT as a daily mean for each bond. That is, 29.3% of all transactions. Based on Feldhütter (2012) and Green et al. (2007), we remove all round-trip trades where the price is equal within the pair. We do not consider such trades to be round-trips but rather immediate matches. We have 5,411 transactions left for further analysis after removing immediate matches.

4.4 The Roll Measure

4.4.1 Calculation of the Measure and Adjustments

The Roll measure was proposed by Roll (1984) for equity markets and later implemented for OTC markets by Bao et al. (2011). The Roll measure exploits that there is a 50% probability of a buy transaction to follow a sell transaction and vice-versa. The idea is that in an efficient market, the true value of a security only changes if any related news occurs. Hence, given no news, the price changes randomly fluctuate between the bid and ask price. As such prices fluctuate around the true price, the observed prices should, in theory, be negatively serially correlated. The measure is interpreted as a transaction cost metric.

The Roll measure relies on historical prices to proxy transaction costs. We need the price for each trade and their exact sequence to compute the covariance between returns. For each transaction in our data set, we create two objects based on the given bond and date in the specific transaction. The covariance between those objects is used in calculating the Roll measure. For the first object, we look back 30 days (approximately 21 trading days) from the given transaction date and include the returns from all transactions that have taken place for the given bond within that time window. The second object, on the other hand, starts the time window at the given bond's second most recent transaction. Consequently, it excludes the most recent transaction and includes all trades 30 days back from the second most recent transaction. The procedure of making these two objects is repeated for each transaction in the data set.

The two objects may comprise a different number of returns depending on how many transactions that have occurred within their specific time window. In such a case, we remove the oldest return observations from the longest object until the longest object equals the length of the shortest. If at least one of the two objects only contains one return observation, the measure cannot be computed. Thus, some transactions are left out. As a result, we reduce the number of applicable transactions from 53,394 to 49,245, leaving us with 92.8% of all transactions to apply the measure. We set the measure to zero whenever the covariance between the two objects is positive, as conducted by both Schestag et al. (2016) and Friewald et al. (2017). Positive covariances cause negative transaction cost estimates, which does not make much sense for Norwegian HY. See Appendix 8.1.2 for a formal description of the formula.

4.4.2 Alternative Calculation

The transaction cost calculated with the Roll measure will somewhat differ depending on the length of the time window. This will impact the number of return observations within the two objects used to compute the covariances. As a robustness check, we have also computed the Roll measure in which we bound each object to comprise exactly four return observations.[11] The first object contains the four most recent returns starting at the given transaction date, and the second object contains the four most recent returns starting at the second most recent transaction. To avoid comparing objects where the time between the included transactions is very long, we require each object to comprise four transactions with a maximum of 30 days between the first and last return within each object. If this constraint is unsatisfied for any transaction, they are left out. The results we present in the forthcoming analysis are practically

[11] Not reported in this thesis.

unaffected depending on which of the calculations we use, indicating that the measure seems robust to the number of transactions to account for when computing the covariances.

4.5 Corwin & Schultz's High-Low Spread Estimator

4.5.1 Calculation of the Measure

The high-low spread estimator (HLS) developed by Corwin and Schultz (2012) uses daily high and low prices as a proxy for the bid-ask spread. They argue that the high prices likely stem from buy orders and that the low prices likely stem from sell orders. The measure exploits the high and low prices for a particular bond and the ratio between them to reflect both the bid-ask spread and the variance. This means that we require at least two trades for a given bond on any given day to obtain both a high price and a low price. Consequently, all transactions in which no other trades exist for the same bond during the same day are removed.

As the bid-ask spread is what we seek to estimate, Corwin and Schultz (2012) present key assumptions to distinguish the bid-ask spread and the variance from each other. The variance is assumed to be proportional to time, while the bid-ask spread is constant. We can separate the two components and calculate the spread by employing time periods of different lengths. Following both Corwin and Schultz (2012) and Schestag et al. (2016), we employ a two-day period. However, due to a relatively infrequent number of transactions for most Norwegian HY bonds, we do not limit the two-day period to compose two consecutive dates. This means that to calculate the HLS, we find the high and low price for a given transaction date and for the previous date where there were at least two transactions for the given bond. This operation is conducted for all transactions.

We require that the high and low prices from the previous transaction date are within 30 days from the given transaction date. This means that, if there for any given day with at least two transactions for a given bond exist no previous days with at least two trades for the same bond during the former 30 days, we leave such transactions out. That is to avoid a too long timespan between the high and low prices. Problems introduced by a long timespan will be addressed in the upcoming section.

The abovementioned filtering leaves us with 8,417 transactions from the original 53,394, which corresponds to 15.8%. For all those transactions, we find the high and low prices for the specific day, the previous day, and for the entire two-day period. The general formula to calculate the HLS based on these values is presented in Appendix 8.1.3.

4.5.2 Adjustments

The stock market in which Corwin and Schultz (2012) present their measure is characterized by two essential assumptions. First, the value of the stocks cannot change while the market is closed. Second, the stocks are traded continuously during market opening hours. This is, of course, not the case for Norwegian HY.

As stated earlier, the variance is assumed to be proportional to time. Thus, the estimator assumes that, over a two-day period, the expectation of a bond's true variance is twice as large as the expectation over a single day. By allowing a gap of 30 days, we substantially increase the probability of a bond being exposed to fundamental price changes between the two days. This involves that the true value, and thus the bond price, may change significantly in the period between the two days. Such a scenario will inflate the high-low price ratio (and variance) for the two-day period compared to the sum of the two one-day periods. This makes the transaction cost estimate negative (as $\beta < \gamma$, see the formula in Appendix 8.1.3). In our case, fundamental price changes between trades are a great problem. As a result, many transactions obtain negative values. If we refrain from making adjustments, 59.6% of the remaining transactions yield negative HLS estimates.

To adjust for the above problem, we follow a procedure suggested by Corwin and Schultz (2012) in which we evaluate, for each two-day period, whether the low price on day t is higher than the close price on the previous day $t - 1$. If that is the case, we assume that the fundamental value of the bond has increased since the previous trading day. Therefore, we calculate the difference between those values and subtract it from the high and low prices on day t. Similarly, the same logic applies if the high price on day t is lower than the close price on the previous day $t - 1$. In this case, assuming that the fundamental value has decreased, we add the difference to the high and low prices on day t. If none of the two abovementioned conditions are true, we make no adjustments. Table 8 summarizes the procedure with an example of which it seems fair to assume a fundamental value decrease. This reduces the number of negative transaction cost estimates from 59.6% to 23.5% of the remaining 8,417 transactions.

Table 8 – 'Overnight' Price Changes Example (COLG15)

	Initial			*Adjusted*		
	t	**t-1**	**Two-day period**	**t**	**t-1**	**Two-day period**
High	58.50	102.00	102.00	102.00	102.00	102.00
Low	57.50	101.75	57.50	101.00	101.75	101.00
Close	58.50	102.00	-	-	-	-
Spread	1.00	0.25	44.50	1.00	0.25	1.00

Table 8 - Illustrative example of price changes during a period where COLG15 by Color Group ASA is not traded. Day t: 2020-03-23. Day $t-1$: 2020-02-28. We observe that $P_{t-1}^{close} > P_t^{high}$. Thus, $\Delta = P_{t-1}^{close} - P_t^{high} = 102 - 58.5 = 43.5$ which gives $Adj\_P_t^{high} = P_t^{high} + \Delta = 58.50 + 43.5 = 102$ and $Adj\_P_t^{low} = P_t^{low} + \Delta = 57.50 + 43.5 = 101$. This adjusts the high low spread estimate from negative (-117%) to positive (0.07%).

4.5.3 Zero and Negative Values

If the transaction cost turns negative, Corwin and Schultz (2012) recommend setting them to zero based on various simulations. They also discuss scenarios of both including or deleting them. However, the fundamental mechanisms of the stock market described by Corwin and Schultz are very different from Norwegian HY. Especially regarding the number of daily trades per bond. We delete both values equal to zero and negative values. The reasoning behind that follows in the two upcoming paragraphs.

The only way a transaction cost estimate can be zero is if at least one of the two days in a consecutive pair has equal high and low prices. Even though equal high and low prices happen, we claim that such a scenario does not imply a transaction cost of zero. Moreover, in the simulations conducted by Corwin and Schultz (2012), the stocks are traded continuously, as opposed to the much more infrequent pattern in Norwegian HY. Thus, a scenario of equal high and low prices for a given day is more likely in our case but does not indicate a transaction cost of 0. Consequently, we delete them.

Negative HLS estimates only occur if the two-day high and low price includes an element from each of the two days. I.e., the high price from one and the low price from the other. This implies that the level of the spread has moved either up or down between the two days. Hence, the total return over the two-day period is large relative to the intraday volatility. Again, we find a transaction cost smaller than a positive number unlikely for the Norwegian HY regardless of a relatively sizeable two-day volatility. Thus, we argue that removing negative values makes more sense than transforming them to zero or including them.

The above implies that the HLS measure troubles in measuring transaction costs in times of crisis for markets where securities are infrequently traded. This usually implies high volatility between days. Before adjusting for fundamental value changes between trading days, many transactions in crises, such as during the COVID-19 outbreak, obtained negative HLS estimates.

The HLS estimator faces various problems in our case, as the paragraphs above highlight. From the initial 53,394 transactions, we conduct the high-low spread calculation on 8,417 transactions where 3,984 are positive, 2,451 are zero, and 1,982 become negative. Hence, only 3,984 transactions are left for further analysis.

Exhibit 1 summarizes the three transaction cost proxies we have established for our liquidity analysis on the overall Norwegian HY market.

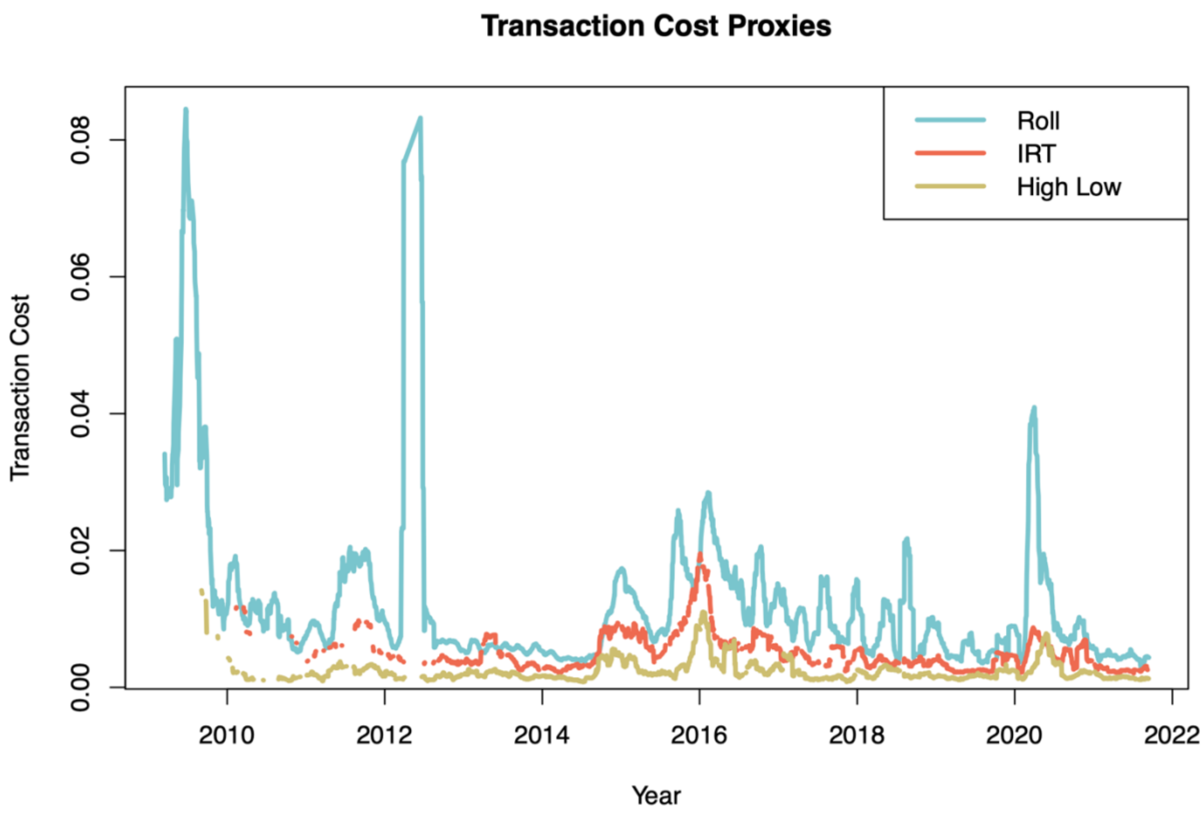

Exhibit 1 – Transaction costs estimates on Norwegian HY from 2009 to October 2021. The time series is calculated as the daily transaction cost mean across all bonds and smoothed by taking the 30-day rolling average. We have left out some observations from 2012 for the Roll measure as its rolling average exceeds 40%. This is only to make the plot tidy.

4.6 Amihud's Measure

4.6.1 Calculation of the Measure

The Amihud measure was presented by Amihud in 2002 and is conceptually based on Albert S. Kyle (1985). In contrast to the previously presented transaction cost measures, the Amihud measure is a price impact proxy. On a daily basis, it relates absolute returns to trading volumes. The measure was initially designed for exchange-traded equity markets. Nonetheless, the measure has become popular for measuring liquidity in OTC markets. The measure is aggregated daily for each bond. After the daily aggregation, we hold 34,203 Amihud values. The formula is displayed in Appendix 8.1.4, where the volume of a transaction is given by the NOK amount.

The idea is that each trade impacts the price of the underlying security. If a bond trades infrequently, each trade plays a more central role in affecting the price of that bond. If the Amihud value is relatively large for a given Norwegian HY bond, trading the bond triggers the price to move more after a certain volume of trading. Consequently, we observe lower liquidity.

4.6.2 Possible Adjustments

As Norwegian HY bonds are traded relatively infrequently during an average trading day, each transaction plays an important role in the daily measure. The mean number of daily trades per bond is 2.4, with a median of 2 and a maximal value of 28. To create a richer foundation of transactions for each Amihud measure, we could aggregate monthly for each bond. However, as we present all other proxies in this thesis in daily terms, we keep the Amihud as a daily measure.

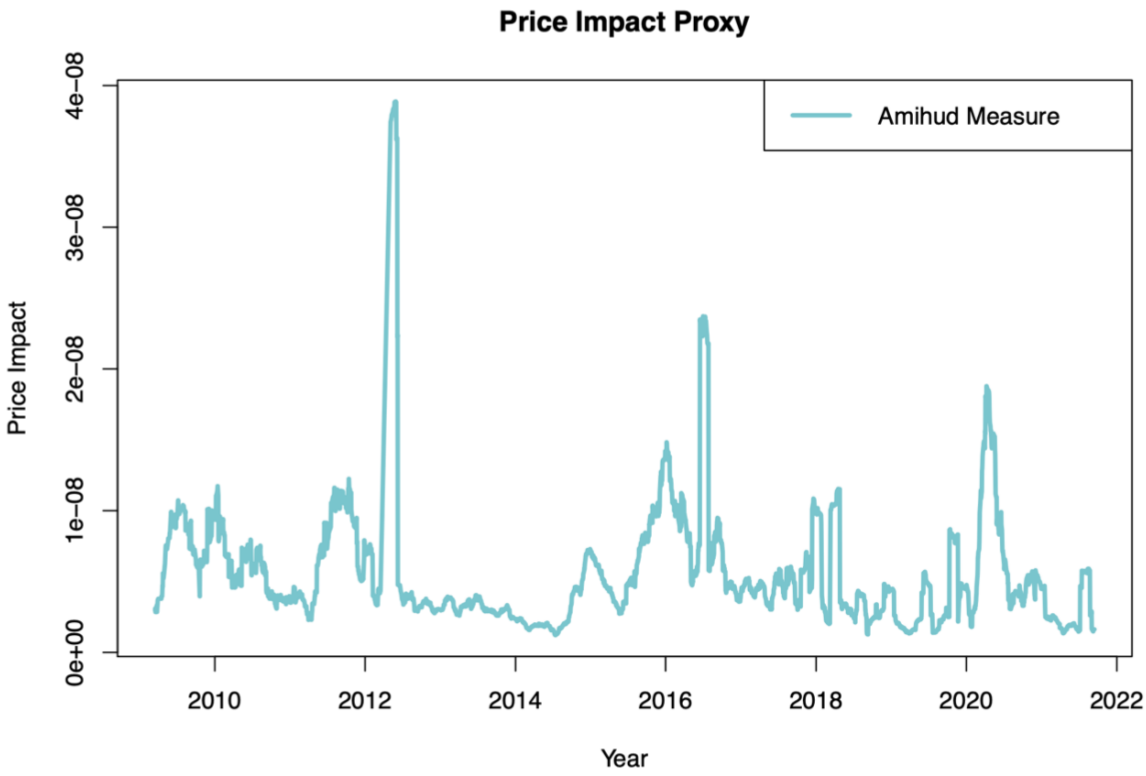

Exhibit 2 – The Amihud measure on Norwegian HY from 2009 to October 2021. The time series is calculated as the daily mean across all bonds and smoothed by taking the 30-day rolling average. As with the Roll measure, we have left out some extreme observations from 2012 in this plot to keep it tidy. The measure is denominated in absolute returns per 1 NOK.

4.7 The Price Dispersion Measure

4.7.1 Calculation of the Measure

The Price dispersion measure (PDM) was introduced by Jankowitsch et al. (2010) as a liquidity measure for OTC markets. The PDM exploits the dispersion between the price of which a security is traded and a market-wide consensus on the value of the same security. In this case, the consensus should, hypothetically, denote the security's fair value. Hence, securities with a high dispersion from consensus trade far from their fair value and are thus considered to have a high trading cost. The volume of the given transaction is used as a weighting factor as it is assumed that dispersion in larger transactions reveals more information. There could be many reasons for price dispersions in a well-functioning market. Among other things, Jankowitsch et al. (2010) demonstrate that in the presence of inventory risk for dealers and search cost for investors, traded prices may deviate from the security's fundamental value.

The PDM is defined as the root mean squared difference between the traded prices and the market-wide consensus prices, weighted by volume (see Appendix 8.1.5). Establishing an appropriate market-wide consensus is essential for the soundness of this measure. Jankowitsch et al. (2010) and Schestag et al. (2016) use composite prices from Markit Group Limited, a financial information provider. Alternatively, Jankowitsch et al. (2010) suggest using mid-quotes from Bloomberg. In a market such as Norwegian HY, it is difficult to collect data on consensus for each bond traded. There are no available composite price data in the Markit Database, and it is hard to extract sufficient information from Bloomberg.

Nordic Bond Pricing (NBP) has priced various Norwegian HY bonds since November 2014 and has provided us with daily theoretical mid-quotes for many of the bonds traded in our data set. This price can be viewed as a market consensus. As an alternative approach, Friewald et al. (2017) use average daily prices for each bond as the consensus. We create two different price dispersion measures based on the two abovementioned proxies for a market-wide consensus. The first is based on the theoretical mid-quote from NBP, while the second is based on the daily mean price for a given bond.

4.7.2 Adjustments

For the NBP approach, we have theoretical mid-quotes since 7. November 2014. Out of the 223 bonds with transactions since that date, we hold daily mid-quotes for 177. This is because we have received daily mid-quotes from NBP for only six sectors. That is, Bank, Industry, Oil & Gas E&P, Oil & Gas Services, Shipping, and Transportation. From the original number of transactions of 53,394, we are left with 25,880 transactions.

For the average price approach, we can work with the entire time series from 2009. However, we require at least two daily transactions to calculate a mean able to trigger any dispersion. Consequently, we remove all transactions where such a transaction was the only one for a given bond on a given day. This operation removes 23,148 rows from the original data frame leaving 30,246 to calculate the PDM. Even though this approach keeps more transactions than the NBP approach, the observations range over almost six additional years, as illustrated in exhibit 3.

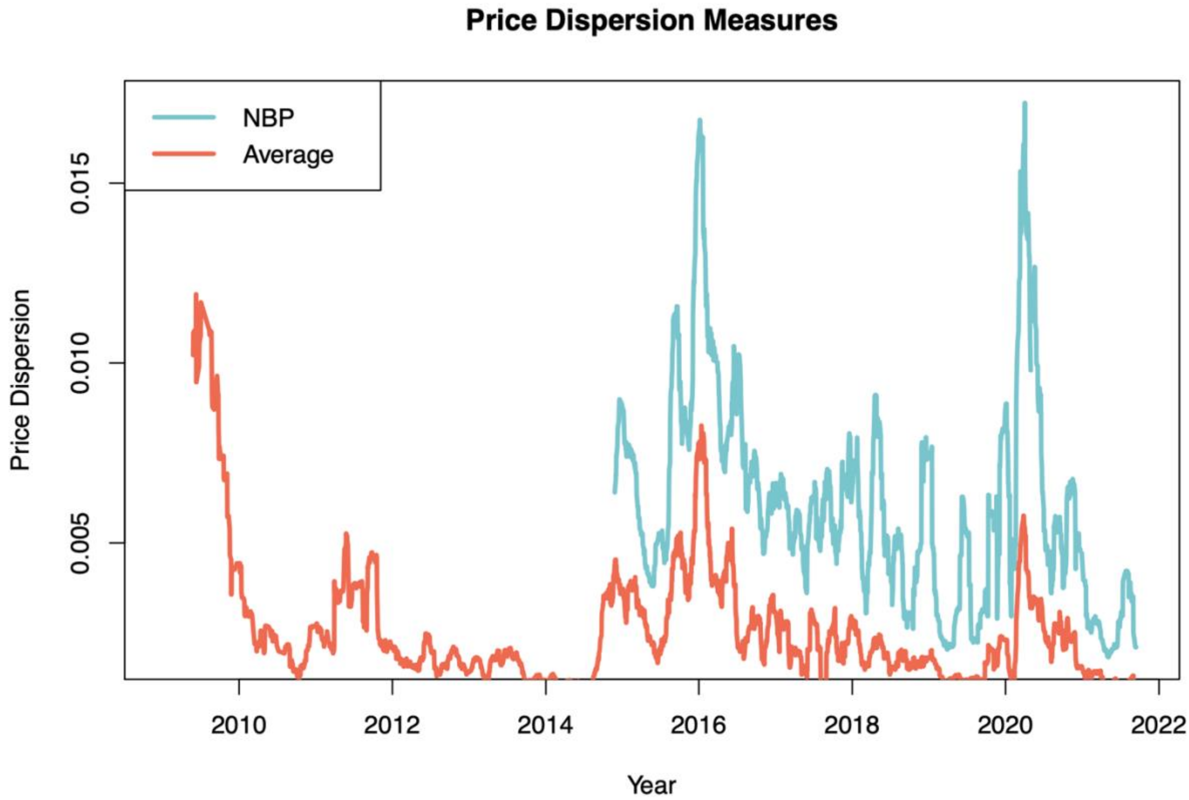

Exhibit 3 – Price Dispersion measure on Norwegian HY from 2009 to October 2021. The time series is calculated as the daily mean across all bonds and smoothed by taking the 30-day rolling average.

4.8 The True Liquidity in Norwegian HY

As Exhibit 1 and 3 display, the directly comparable measures estimate liquidity quite differently. We find it important to emphasize that we cannot say how the true liquidity has been, and we do not precisely know which measures perform best in estimating it for Norwegian HY. In the forthcoming regressions, we treat each measure as the actual liquidity and discuss the observed differences between them. The purpose of this thesis is to establish estimates on the size of the average liquidity premium, and the observed results from several of the liquidity measures will be applied to do so.

5. Analysis

5.1 Descriptive Analysis

In this section, we start by evaluating the Norwegian HY market based on trading frequency and trading volume. After that, we discuss the results obtained from the various liquidity measures for the entire HY market and the five most frequently traded sectors. That is Shipping, Oil and Gas Services, Oil and Gas E&P, Industry, and Transportation. After examining the results from the measures, we investigate the correlation between them.

5.1.1 Trading Frequency and Volume

Tables 9 and 10 present bond trading frequency based on two different approaches. Common for both is that, for each bond, we estimate an appropriate time window in which the given bond is evaluated. The time window for each bond starts with the date the bond first traded and ends at the last trading date in the transaction data. That is unless the bond has already matured. In that case, we end the time window half a year before the given maturity date as we removed all transactions for bonds with less than half a year to maturity in section 3.2.

For the first approach, presented in Table 9, we find the number of transactions for a given bond and divide by the relevant time window. For instance, if a bond is traded eight times over four years, this bond will, on average, trade twice a year. Even though all eight transactions occurred during the same year, that will be the case. The second approach, presented in Table 10, is more restrictive and would not count such a bond. Here, the bond must trade in each year within its time window to be accounted for. Looking at the changes between the tables, we observe important differences as Table 10 reflects a less active market than Table 9 indicates. For instance, Table 9 shows that 83.53% of all bonds are, on average, traded once a month. Table 10, on the other hand, displays that only 9.41% of all bonds are traded at least once in each of its relevant months. Based on these differences, transactions seem to cluster.

Table 9 – Average Trading Frequency		
Minimum Frequency	**Number of bonds**	**Proportion of all bonds** [%]
Once yearly on average	337	99.12
Once monthly on average	284	83.53
Once weekly on average	117	34.41
Once daily on average	0	0.00

Table 9 - Trading frequency on year, month, week, and day based on each bond's total number of transactions divided by the relevant time window. The time window is from its first transaction to the last date in the transaction data, 2021-10-05. If matured, the end of the time window is 0.5 years before maturity.

Table 10 – Trading Frequency		
Minimum Frequency	**Number of bonds**	**Proportion of all bonds** [%]
Once each year	272	80.00
Once each month	32	9.41
Once each week	0	0.00

Table 10 - Trading based on yearly, monthly, and weekly frequency. For a bond to qualify, it must have been traded for each year/month/week since its first transaction until the last date in the transaction data, 2021-10-05. If matured, the end of the time window is 0.5 years before maturity.

Table 11 exhibits the number of daily trades, the daily traded million NOK amount, and each of the liquidity measures for the main sectors. We observe that, across all sectors in Norwegian HY, there is an average of 16.04 daily trades and an average daily trading volume of 6.23 million NOK. The averages are computed based on all trading days since the start of the time series. This includes all trading days in which no transactions have been executed. The total outstanding volume in Norwegian HY in 2021 was approximately 289 billion NOK. Hence, the average daily trading volume corresponds to an average daily turnover equal to approximately 0.0022% of the total current market size. Again, we do not hold information on all trades conducted in Norwegian HY due to the weak historical reporting policy, meaning that the actual turnover should be somewhat higher to an unknown extent.

Table 11 - Characteristics and Liquidity

	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
	All sectors		Shipping		Oil & Gas Services		Oil & Gas E&P		Industry		Transportation	
Panel A: Characteristics												
Number of daily trades	16.04	12.15	4.34	4.46	4.13	5.10	1.20	2.13	3.13	3.26	1.39	1.98
Daily trading volume [M.NOK]	6.23	7.34	5.00	9.94	4.44	12.15	3.68	15.42	4.03	6.58	2.19	5.62
Panel B: Liquidity Measures												
Imputed round-trip cost [%]	0.49	0.98	0.33	0.75	1.05	1.69	0.35	0.61	0.36	0.43	0.34	0.34
Roll measure [%]	1.33	21.35	0.66	1.47	3.17	41.78	0.79	2.03	0.70	1.06	0.64	1.25
Corwin Schultz [%]	0.24	0.52	0.15	0.17	0.42	0.90	0.16	0.15	0.18	0.27	0.17	0.19
Amihud [%/M.NOK]	0.68	29.62	0.33	1.23	1.63	58.59	0.41	1.43	0.36	0.90	0.35	0.79
Price dispersion (NBP) [%]	0.64	1.78	0.35	0.66	1.72	3.57	0.42	0.65	0.37	0.44	0.38	0.59
Price dispersion (Mean) [%]	0.24	0.56	0.16	0.37	0.44	0.94	0.18	0.44	0.17	0.26	0.16	0.22

Table 11 – Trading characteristics and liquidity measures for each main sector in Norwegian HY.

The number of trades and the daily turnover indicate low market activity. In comparison, the average daily turnover in 2017 for the U.S. Structured Product Market was 0.32%, and the corresponding figure for the U.S. Treasury Securities Market was 4.70% (Friewald et al., 2017). Those figures are, respectively, 150 and 2200 times larger than we observe for Norwegian HY.

Furthermore, according to Bao et al. (2011), the average monthly turnover for U.S. corporate bonds (TRACE) was 3.71% between 2003 and 2009. That is a bond's monthly trading volume as a percentage of its issuance size. Further, the average number of trades for a bond in a month was 33. In Norwegian HY, on the other hand, related figures turn out considerably lower. The former corresponds to 1.01% and the latter to an average of 5.76 trades per bond per month. However, the Norwegian figures are based on months in which at least one trade for the given bond was executed. This involves that all zero-trade months are ignored. We see from Table 10 that only 9.41% of Norwegian HY bonds are traded at least once every month. Despite the less restrictive computation of the averages, Norwegian figures still turn out lower. This entails that the trading activity in Norwegian HY is substantially lower than for U.S. corporate bonds.

To sum up, by evaluating the trading frequency and volume in Norwegian HY, all statistics point toward a low-activity market which usually is an indication of illiquidity.

5.1.2 Liquidity in Norwegian HY

Transaction cost proxies

Panel B in Table 11 exhibits the average results obtained by the various liquidity measures applied to the transaction data for Norwegian HY. The transaction cost proxies, IRT, Roll, and Corwin & Schultz deviate considerably across all sectors. The former estimates a transaction cost of 49 bp, the second of 133 bp, and the latter suggest 24 bp. The Roll measure is particularly noisy, with a standard deviation of 2,135 bp, mainly driven by the Oil & Gas services sector. This sector has been the most volatile in terms of price changes. During the falling oil prices between 2014 and 2016, many oil service companies struggled and thus experienced reduced value on their debt. This was also the case for companies within Oil & Gas E&P sector, but the value decrease on their debt was less severe. The recent outbreak of COVID-19 has also led to relatively high price volatility. However, this crisis is broader, and the other sectors are equally exposed. Nevertheless, The Roll measure is most sensitive to fundamental price changes among the transaction cost proxies and thus presents relatively noisy estimates.

The IRT and Corwin & Schultz present more similar estimates. Both measures are less exposed to fundamental changes in the debt value. As elaborated in section 4, the former is based on intraday transactions, while the latter is adjusted for 'overnight' price changes. As a result, their estimates are less noisy. However, not necessarily true. The variation between the measures for the entire market and between sectors implies no firm conclusion on the transaction cost within Norwegian HY. According to our estimates, it lies somewhere between 24 and 133 bp. Nonetheless, what appears to be clear is that the Oil and Gas Services sector is less liquid than the other four which all obtain quite similar transaction cost estimates based on each measure.

Amihud

As with the Roll measure, Amihud comprises much noise. The measure estimates an average absolute price change of 0.68% for a one million NOK transaction. This implies that for the mean daily trading volume at 6.2 million NOK, the Amihud estimates a price impact of 4.24%. A larger Amihud value indicates lower liquidity as the bond's price moves more in response to a specific volume. Like the transaction cost proxies, we observe that Amihud points out the Oil & Gas Services sector as the least liquid while keeping the other four at a similar level.

Price dispersion measures

The price dispersion measures also display the same pattern for the various industries as the liquidity measures mentioned above. The PDM based on NBP mid-quotes presents a price dispersion of 64 bp, while the mean-based approach estimates 24 bp. In comparison, Friewald et al. (2012) reported a market price dispersion at 42 bp, on average, for the U.S. Corporate Bond Market. Within all sectors, the NBP approach is always above the mean-based version. Since the former bases the consensus price on theoretical values calculated by NBP, we cannot say precisely why this is the case. However, it implies that NBP tends to estimate the consensus price as 'more extreme' than the intraday mean.

The relatively low number of daily trades for Norwegian HY bonds could make the mean-based approach less efficient. The mean number of daily trades per bond is 2.6.[12] When calculating a consensus based on the mean of only two or three trades, the output is heavily influenced by individual transactions. The price dispersion will be low when applying a consensus highly influenced by the price of that specific transaction. Therefore, the NBP is valuable as a comparison for the mean-based approach which perceives Norwegian HY as considerably more liquid.

5.1.3 Correlation Between the Liquidity Measures

In this section, we investigate the correlation between the various liquidity measures. Tables 12 and 13 present the correlations daily and monthly, respectively. We exploit pairwise complete observations for the calculations. Thus, to calculate the correlation between two given measures, both must have an estimate for the given day/month. Exhibit 4 summarizes the results graphically.

We observe a positive correlation between most of the measures. Especially the NBP-based PDM correlates relatively strongly with all the others. We also observe some measures which seem to capture vastly different variations, such as Amihud compared to either IRT, Corwin & Schultz, or the mean-based NBP. In general, as the liquidity measures quantify somewhat different variations, they appear to capture various aspects of liquidity in Norwegian HY. This will be a topic for upcoming regressions in section 5.2.

[12] Based on the transactions included in the calculation of the mean-based PDM measure, as described in section 4.7

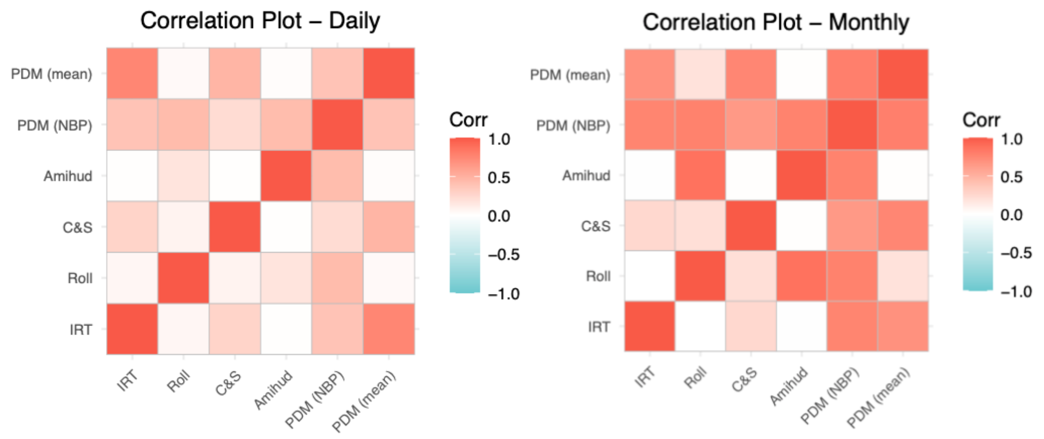

Exhibit 4 - Correlation plots. Left: Daily frequency. Right: Monthly frequency.

Table 12 - Correlation Matrix in % (Daily Frequency)

	IRT	Roll	Corwin & Schultz	Amihud	PDM (NBP)	PDM (Mean)
Imputed round-trip cost						
Roll measure	6.14					
Corwin Schultz	28.08	7.72				
Amihud	1.09	18.23	0.57			
Price dispersion (NBP)	38.69	43.76	23.12	43.05		
Price dispersion (Mean)	76.08	3.59	47.85	2.37	38.92	

Table 12 - Correlation matrix daily.

Table 13 - Correlation Matrix in % (Monthly Frequency)

	IRT	Roll	Corwin & Schultz	Amihud	PDM (NBP)	PDM (Mean)
Imputed round-trip cost						
Roll measure	0.22					
Corwin Schultz	24.95	21.44				
Amihud	-0.69	87.20	1.10			
Price dispersion (NBP)	76.53	78.94	65.16	78.01		
Price dispersion (Mean)	69.62	19.31	76.43	1.01	79.63	

Table 13 - Correlation matrix monthly.

5.2 Empirical Analysis

In the two upcoming sections, we present the results of our empirical analyses. Section 5.2.1 analyzes the observed relation between the liquidity measures and various characteristics. By looking at characteristics' relation to liquidity, we aim to establish some easy observable proxies for liquidity in Norwegian HY. Section 5.2.2 explores how liquidity is related to bond prices in Norwegian HY by examining how liquidity measures empirically explain variation in the yield spread. This lets us explore whether liquidity is reflected in prices in Norwegian HY, which is the primary purpose of this thesis. According to Stensaker (2021), market participants perceive the market as relatively illiquid. Thus, we expect to find a significant liquidity premium.

5.2.1 Liquidity Effects in the Norwegian High Yield Market

To analyze the observed relation between various characteristics and the liquidity measures, we run a panel data regression on each liquidity measure using month fixed effects and robust standard errors clustered on issuer and month.[13] Fixed effects are used because we are interested in cross-sectional differences. Thus, by accounting for month fixed effects, we try to avoid time-specific changes in the general liquidity level corrupting the cross-sectional analysis. We use clustered standard errors to avoid biased estimates of the standard errors as we believe the variation to be correlated across issuer and time.

We run the regression on daily averages for all numerical variables. The correlation matrix in section 5.1.3 shows that the extent of correlation between the various liquidity measures varies. This implies that the measures may explain different aspects of liquidity. For example, the IRT cost is a sheer estimation of the transaction cost, while Amihud measures a broader impact from a trade on the price. Thus, running the regression on all six liquidity measures separately lets us analyze the effect on a broad specter of liquidity. We include bond characteristics and trading activity variables as explanatory variables in the regression. For bond i at time t, we specify the regression as displayed in equation 2.

[13] The month variable for both fixed effect and clusters are depending on year, e.g., January 2013 is different from January 2014.

$$liquidity\ measure_{it} = \alpha_0 + \sum_j \beta_j \cdot Bond\ Characteristic_{ijt} + \sum_k \delta_k \cdot trading\ activity_{ikt} + \sum_m k_m \cdot month_{mt} + \epsilon_{it} \quad (2)$$

We run the regression on daily observations. However, there is a frequency trade-off between using more frequent data, which gives more statistical power but also implies larger measurement error and can cause unbalanced data. Therefore, we have copied the regression presented in this section and performed it on monthly averages to check how robust the results are to data frequency effects. See Appendix 8.2.1 for regression table on monthly data. It seems like the choice of data frequency does not affect the results considerably.

Variable Selection

Bond characteristics include *Time to Maturity*, *Outstanding Amount*, *Coupon Rate*, *Credit Rating*, *Age*, and *Sector.* We presume that bonds with a relatively short *Time to Maturity* are more liquid as their bullet payment is closing in.[14] Moreover, we believe that bonds with a long time to maturity more often are held by 'buy-and-hold' investors. According to Mahanti et al. (2008), bonds held by such investors are generally less accessible and thus considered to be less liquid. *Outstanding Amount* is included to account for the bonds' size. It seems reasonable that a sizeable outstanding amount is connected to more investors holding the bond, which potentially could have a positive relationship with liquidity.

We also include *Credit Rating* as a proxy for the credit risk.[15] A study by Diaz and Escribano (2019) shows that credit risk and liquidity in bond markets are negatively correlated. Regarding the inclusion of *Age*, we believe that bonds are more liquid close to the issuing date. Especially bonds that end up in long-term portfolios among low-turnover investors. Further, we include *Coupon Rate* as this is a key bond characteristic for many investors. Lastly, based on our descriptive analysis in section 5.1, we include a *Sector* dummy to control for sector-specific effects as the Oil & Gas Sector seems to be less liquid.

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[14] Remark that we only consider bullet bonds, as described in section 3.2.

[15] *Credit Rating* should only be considered a crude proxy to credit risk as it merely accounts for a company's probability of default. We will elaborate on shortcomings of this variable in section 5.2.2.

As previously mentioned, trading activity is often an indicator of liquidity. Hence, we expect some correlation between a bond's liquidity and its trading activity. Thus, we include various trading activity variables in our regression model. Those include *Volume*, *Days Since Last Transaction*, and *Number of Trades* on a given day for a bond. We expect that bonds with high trading activity, on average, are more liquid.

Table 14 – Liquidity Measures (Daily)	Roll Measure (1)	IRT Measure (2)	Corwin & Schultz (3)	Amihud Measure (4)	PDM NBP (5)	PDM Avg (6)
Trading activity variables						
Volume	-0.003	-0.003***	-0.001*	-0.009**	-0.001	-0.001**
	(0.173)	(0.001)	(0.081)	(0.027)	(0.565)	(0.042)
Days Since Last	0.021	0.009**	-0.004	0.018***	0.016***	0.002*
Transaction	(0.115)	(0.032)	(0.155)	(0.001)	(0.001)	(0.086)
Number of	0.017	-0.007	0.015**	-0.060	0.004	0.027***
Trades	(0.892)	(0.381)	(0.014)	(0.504)	(0.708)	(0.000)
Bond Characteristics						
Coupon Rate	0.061	-0.011	-0.006	-0.081	-0.059	-0.008
	(0.796)	(0.570)	(0.608)	(0.516)	(0.268)	(0.388)
Time to Maturity	0.276**	0.085***	0.046***	0.267**	0.174***	0.033**
	(0.030)	(0.000)	(0.000)	(0.016)	(0.005)	(0.012)
Outstanding	-0.436*	-0.035	-0.034	-0.390**	-0.073	-0.028
Amount	(0.098)	(0.226)	(0.200)	(0.033)	(0.388)	(0.132)
Age	-0.051	0.032*	0.018	0.051	0.047	0.003
	(0.610)	(0.064)	(0.117)	(0.291)	(0.183)	(0.719)
Credit Rating B	-0.061	0.023	0.119*	0.108	0.206	0.089
	(0.871)	(0.857)	(0.068)	(0.365)	(0.383)	(0.136)
Credit Rating C	0.117	0.035	0.161**	0.340	0.211	0.102*
	(0.802)	(0.726)	(0.022)	(0.126)	(0.425)	(0.072)
Credit Rating D	1.586**	0.170	0.227***	0.975*	0.421*	0.185***
	(0.012)	(0.141)	(0.004)	(0.073)	(0.084)	(0.006)
Credit Rating E	4.929*	0.480**	0.363***	3.751	1.227**	0.304**
	(0.099)	(0.017)	(0.000)	(0.137)	(0.032)	(0.013)
Credit Rating F	0.303	0.434	0.239	0.778	0.969	0.241*
	(0.722)	(0.259)	(0.121)	(0.134)	(0.256)	(0.072)
Sector Dummies	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	30,924	4,784	3,981	34,200	15,969	11,624
R2	0.023	0.257	0.208	0.007	0.177	0.140
Adj. R2	0.017	0.230	0.173	0.002	0.172	0.127
Std. Errors	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month

*P-values in parentheses (the significance levels are denoted as * = 10%, ** = 5% and *** = 1%)*

Table 14 - Regressing the Roll measure, Imputed Round Trip cost, Corwin & Schultz's High-Low Spread Estimator, Amihud measure, and the two Price Dispersion measures on trading activity variables and bond characteristics using a panel data regression with month fixed effects and robust standard errors clustered on issuer and month. Values in parentheses are the p-value. All liquidity measures are in percentage, except the Amihud measure, which is in units of percentages per one million NOK. Trading Volume is in units of million NOK and *Outstanding Amount* in billion NOK. The numerical variables are daily averages.

Results

The results are presented in Table 14. When referring to a significant result, we use the 5% level. *Volume* is negatively correlated with liquidity. For example, on average, a one standard deviation increase in trading volume decreases the IRT cost by 6.5 bp. We observe that *Volume* is significantly different from zero for three out of six measures. Regarding *Days Since Last Transaction* an additional day since the previous transaction took place seems to reflect lower liquidity for most measures.

A more surprising result is that an increase in the *Number of Trades* for a bond on a given day is associated with lower liquidity in most regressions, whereas two are significant. Looking at the regression for Corwin & Schultz, a one standard deviation increase in the number of daily trades for a bond is associated with an increase in transaction cost by 17.1 bp. This is the opposite of what we expected. However, Dick-Nielsen et al. (2012) show that the number of trades in illiquid bonds may increase during times of crisis as trades are split into trades of smaller size. Our dataset starts at the end of the Great Recession, goes through the oil crisis in the mid-2010s, and ends with the COVID-19 outbreak. In other words, there have been several crises that can substantiate this surprising result.[16] Albeit there is uncertainty linked to this result as four of the regressions yield results that are not significantly different from zero.

Among the bond characteristics, *Time to Maturity* is significantly positively correlated with all the liquidity measures. For instance, an increase of one standard deviation in *Time to Maturity* increases the expected transaction cost by 27.1 bp for the PDM (NBP) measure. Next, an increase in the *Outstanding Amount* is related to a bond being more liquid. However, a one standard deviation change is only associated with an increase in the expected PDM (Avg) at 2.3 bp. We thus find the economic significance to be minor. Likewise, *Age* and *Coupon Rate* are neither economically nor statistically significant in any regressions.

[16] Additionally, an Australian study conducted by Lien and Zurawski (2012) shows that investors may hedge their positions more frequently in times of uncertainty, which could lead to a higher number of transactions in times of crisis.

The dummy variables for the credit rating groups show that the lower rating groups (D, E, and F) are associated with lower liquidity than the firms with better credit ratings. These three rating levels have between 42.1 and 122.7 bp higher transaction costs than rating group A for the PDM (NBP) measure. There are few issuers with a rating of F, which makes it hard to obtain a statistically significant coefficient for this rating group. However, the expected difference between the lower rating groups and the issuers with the best credit rating is of considerable economic importance.

Oil and Gas Services is the least liquid sector. This is in accordance with our descriptive analysis in section 5.1. Compared to the base sector, which is Bank, Oil and Gas Services are expected to have 68.2 bp higher transaction cost. The coefficients are positive in all regressions and statistically significant in five out of six. This is after we have accounted for credit risk by *Credit Rating*. Thus, in theory, the differences between sectors should not be due to differences in credit risk between sectors.[17] There are no other noteworthy differences in liquidity between the rest of the sectors.

Our results show that certain bond characteristics and trading activity variables are related to liquidity and can, to some extent, be used as proxies for liquidity by market participants. *Time to Maturity*, *Credit Rating,* and *Days Since Last Transaction* appears to be the most central variables. Additionally, the Oil and Gas Services sector is significantly less liquid than all other sectors. We also find interesting effects from the *Number of Transactions*. Two regressions indicate that more trades are significantly related to a bond being less liquid. The adjusted R2 of the regressions varies from 0.2% for Amihud to 23.0% for the IRT. This indicates considerable unexplained variation regardless of which liquidity measure we use as the response variable. This could be due to other factors not included in this analysis related to the liquidity in Norwegian HY. Alternatively, that the liquidity measures are imprecise in estimating the true liquidity.

[17] Again, *Credit Rating* does not reflect all aspects of credit risk and should thus only be considered a crude proxy. Hence, after all, differences between sectors may be affected by some sector-specific credit risk.

5.2.2 Liquidity and the Yield Spread

This section provides insights into how liquidity affects the compensation investors require for holding a bond. Originally the credit component of the yield spread was viewed as a premium that was entirely due to expected loss. This view has changed, and several studies show that there is more to the credit component than default risk. Sæbø (2015) finds that the expected loss constitutes 46% of the total credit spread in Norwegian HY, leaving the remaining 54% for other factors. Liquidity is expected to be one of those factors. Improved liquidity decreases the compensation investors require for holding a bond, leading to an expected negative relationship between the yield spread and liquidity. Thus, we expect liquidity to describe some of the variations in the yield spread.

We conduct the analysis by looking at the observed relation between the yield spread and the liquidity measures. We use a panel data regression with month fixed effect and robust standard errors clustered on issuer and month for the same reasons described in section 5.2.1. Running the yield spread on each liquidity measure allows us to empirically test how liquidity correlates with the yield spread and whether liquidity influences the pricing of bonds in Norwegian HY. We also explore how much of the total variation in the yield spread we can explain with a richer model by employing all liquidity measures and certain bond characteristics. For the full model, we primarily focus on the adjusted R2. The model is specified as displayed in equation 3.

$$yield\ spread_{it} = \alpha_0 + \sum_j \beta_j \cdot liquidity\ measure_{ijt} + \sum_k \gamma_k \cdot control\ variable_{ikt} + \sum_m k_m \cdot month_{mt} + \epsilon_{it} \tag{3}$$

We run the regression on daily averages of the numerical variables and once again use monthly averages as a robustness check. Again, there are no noteworthy differences. See Appendix 8.2.2 for the monthly regression table.

Variable selection

Regarding the full model, we exclude trading activity variables as their effect on the yield spread, in theory, should be reflected through the liquidity measures. We do not believe there are other, separate effects from trading activity on the yield spread. On the other hand, certain bond characteristics have additional effects other than through liquidity.

Credit Rating should capture some of the correlations between the yield spread and the probability of default. *Coupon Rate*, *Outstanding Amount,* and *Age* are also variables we include as they might capture variations describing the yield spread of a particular bond. Furthermore, we expect that *Time to Maturity* has a relation to the yield spread. Fama and Bliss (1987) find a significant non-zero and time-varying term premia from 1965 to 1985. Later other studies come to similar conclusions.[18] These empirical studies demonstrate that longer maturity bonds, in most cases, trade at a premium to short-maturity bonds due to the distant future being more uncertain than the non-distant.

Multicollinearity between the various liquidity measures in the full model is an issue that should be addressed. However, we primarily emphasize the adjusted R2 measure for the full model. By including all liquidity measures, we account for a broader specter of liquidity compared to solely using one.

[18] Gil-Alana & Moreno (2012) and Campbell & Shiller (1991) support these findings.

Table 15 – Yield Spread (Daily)

	Yield Spread						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Liquidity Measures							
Roll	2.03						102.56***
	(0.249)						(0.001)
IRT		797.89***					77.99
		(0.000)					(0.420)
Corwin & Schultz			957.68***				704.78***
			(0.000)				(0.005)
Amihud				0.67			-166.65***
				(0.360)			(0.004)
PDM NBP					404.93***		451.23***
					(0.000)		(0.000)
PDM Ave						924.91***	-87.74
						(0.000)	(0.812)
Bond Characteristics							
Coupon Rate							31.85
							(0.413)
Time to Maturity							-80.67**
							(0.042)
Outstanding Amount							0.00
							(0.230)
Age							35.81
							(0.339)
Credit Rating B							444.36
							(0.167)
Credit Rating C							615.51*
							(0.095)
Credit Rating D							548.28
							(0.162)
Credit Rating E							1207.25
							(0.185)
Credit Rating F							1165.76***
							(0.006)
Month FE	YES	YES	YES	YES	YES	YES	YES
Obs.	30,822	4,685	3,926	34,066	15,897	11,229	1,195
R2	0.071	0.292	0.275	0.067	0.253	0.216	0.579
Adj. R2	0.066	0.269	0.247	0.063	0.249	0.205	0.541
Std. Errors	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month

*P-values in parentheses (the significance levels are denoted as * = 10%, ** = 5% and *** = 1%)*

Table 15 - The table reports the result of regressing the yield spread on the Roll measure, Imputed Round Trip cost, Corwin & Schultz's High-Low Spread Estimator, Amihud measure, and the two Price Dispersion measures using a panel data regression with monthly fixed effects and robust standard errors clustered on issuer and month. In regression 7, bond characteristics are included as control variables. Values in parentheses are the p-value. All liquidity measures are in percentages, except the Amihud measure, which is in units of percentages per one million NOK. Trading Volume is in units of million NOK and *Outstanding Amount* in billion NOK. The numerical variables are daily averages. Finally, we obtain slightly fewer observations in this regression compared to 5.2.1 because the *Spread* variable lacks 305 values.

Results

The results are presented in Table 15. Regression 1 to 6 employs each liquidity measure individually. Regressions 2, 3, 5, and 6, using IRT, Corwin & Schultz, and the two PDM measures, show that liquidity is a significant variable in explaining the yield spread. For instance, for Corwin & Schultz, a one standard deviation increase in the transaction cost increases the yield spread by 498 bp. The adjusted R2 for these four regressions lies between 20.5% and 26.9%, indicating that liquidity is an important factor in explaining the variation in the yield spread.

Neither Roll nor Amihud, in regression 1 and 4, is significantly different from zero or capable of explaining a notable share of the variation in the yield spread. The adjusted R2 for Roll is 6.6%, while Amihud obtains an adjusted R2 of 6.3%. Schestag et al. (2016) conclude that standard price impact measures, such as the Amihud measure, are not able to consistently proxy for the slope of the price function in the bond market. In addition, Friewald et al. (2017) find that IRT and PDM are better at explaining price-relevant information for the U.S. Structured Product Market than the Amihud and the Roll measure. We choose to weigh the result of regressions 2, 3, 5, and 6 heaviest, as the mentioned studies recommend these measures over Roll and Amihud.

Regression 7 includes all liquidity measures and certain bond characteristics. The coefficients of the liquidity measures do not turn out to be significant for the same measures as for the individual regressions. This is likely due to multicollinearity, as all measures explain some of the same variations. The adjusted R2 increases to 54.1%. Hence, liquidity and bond characteristics seem to explain roughly half of the variation in the yield spread.

The above entails a relatively large share of unexplained variation in the yield spread, which is somewhat surprising given the variables we include in the regression. However, the expected loss component is weakly represented for two main reasons. First, we lack a loss given default component. Second, the *Credit Rating* variable does not reflect a time-varying probability of default as the ratings are constant throughout the entire period. It is unlikely that the probability of default for all companies remains unchanged for the whole period. The importance of expected loss in the yield spread is undisputed, especially for high yield bonds. The two mentioned shortcomings demonstrate that the *Credit Rating* variable is not able to capture important variation regarding the expected loss of a bond. Additionally, there presumably exist other variables that describe the yield spread that we do not have data for or are unable to detect.

Despite the shortcomings discussed above, companies with poorer *Credit Rating* are associated with a higher yield spread. A bond issued by a company with a rating of F is expected to have a 1,166 bp higher yield spread than a similar bond issued by an A-rated company. This coefficient is significantly positive. On the contrary, neither *Coupon Rate*, *Outstanding Amount,* nor *Age* is significant in impacting the yield spread. However, the low number of observations in the full model makes it hard to get statistically significant results.[19]

Time to Maturity turns out negative, meaning that an increase in maturity gives a decrease in the yield spread, everything else equal. This contradicts our discussion above regarding a positive term premium. With a p-value of 4.2%, we can significantly state that the coefficient we obtain is negative. In supporting such a scenario, Fama and Bliss (1987) find that the term premia can be negative. Especially in times when the business environment turns 'sour'. As previously mentioned, our dataset includes three substantial crises. Thus, a negative term premium could make sense in Norwegian HY for the analyzed period.

To conclude this section, we find that investors require a considerable premium for the illiquidity in Norwegian HY. The measures that are significantly different from zero explain between 20.5% and 26.9% of the variation. That is the IRT, Corwin & Schultz, and the two PDM measures. As a result, our estimate on the size of the average liquidity premium in Norwegian HY is within this interval as a proportion of the yield spread.

[19] The reason why the full model has few observations is that it is only possible to run for days where all the liquidity measures give an estimate.

6. Conclusion

Norwegian HY has grown to become an important source of capital for many companies. The total outstanding amount has doubled during the last decade, making it the largest HY market in the Nordics. However, according to Stensaker (2021), it is perceived as illiquid by several market participants. In this thesis, we analyzed liquidity effects in Norwegian HY by looking at characteristics related to liquidity. Ultimately, how liquidity affects the pricing of bonds by examining how much of the variation in the yield spread that can be explained by the illiquidity.

In the descriptive analysis, we established that the trading activity in Norwegian HY is low compared to both the U.S. Corporate Bond Market and the U.S. Structured Product Market. We found Norwegian HY's daily average trading volume to be approximately 6.23MNOK, which corresponds to a daily turnover equal to about 0.0022% of the total current market size.

The available transaction data for Norwegian HY is limited as the bonds trade in a relatively opaque OTC market. Consequently, many traditional liquidity measures, such as the bid-ask spread, are unavailable. Therefore, we employed six alternative liquidity measures proposed in the academic literature for the empirical analysis of liquidity to investigate the liquidity premium. Three measures are transactions costs proxies, one measure estimates price impact and the remaining exploits price dispersion.

The average transaction cost across the three relevant measures is 69 bp. We found Oil and Gas Services to be the least liquid *Sector*. Unsurprisingly, the trading activity variables *Volume* and the number of *Days Since Last Transaction* are both related to how liquid a Norwegian HY bond is. Of bond characteristics, *Time to Maturity* and *Credit Rating* came out as the two most important variables. On average, bonds with poorer credit ratings are less liquid, and bonds tend to become more liquid as they close in on their maturity date.

Exploring the relation between liquidity and the yield spread, we found a significant correlation between less liquid bonds and a higher yield spread. The liquidity measures show varying capability of explaining the variation in the yield spread. Nonetheless, those significantly different from zero explain between 20.5% and 26.9% of the variation, meaning investors in Norwegian HY require a considerable premium for the illiquidity. As a result, our estimate on the average liquidity premium in Norwegian HY is between 20.5% and 26.9% of the yield spread.

7. Limitations and Further Research

7.1 Latent Liquidity

Mahanti et al. (2008) elaborate on shortcomings in measuring liquidity by using transaction data for relatively illiquid markets with low trading activity. The authors present an alternative liquidity measure based on investors' portfolios and their turnover without considering transaction data. The paper defines latent liquidity as the weighted average turnover of investors who hold a bond, in which the weights are the fractional investor holdings. This implies that a bond can be liquid even though not traded. Liquidity is thus determined by the accessibility of a security in terms of the sources that hold the bond at a given moment, as exemplified with hedge- and pension funds in section 4.1. The latent liquidity measure would be highly valuable given the characteristics of the Norwegian HY market. Additionally, it would neutralize the loose historical reporting policy of transactions.

Ideally, we would have access to all investors' holdings and the changes in their holdings to determine the latent liquidity of each issued bond within the HY market. With such access, we could also quantify a liquidity measure for bonds with very few or no registered transactions. However, this is not the case. In an attempt to partly deal with such an effect, we have created synthetic bonds composed of real bonds with similar characteristics. If a bond has a similar bond that is traded more frequently and obtains lower liquidity measure values, one could argue that both bonds should be approximately equally liquid. Similar bonds are probably held by relatively similar investors making the bonds approximately equally accessible. We treat the synthetic bonds as *one* regular bond in the liquidity calculations.

By creating synthetic bonds, we have reduced the number of bonds from the original 340 to 136. Bonds within a synthetic bond are considered similar based on *Sector*, *Time to Maturity*, *Credit Rating*, *Country, Coupon Type,* and whether the bond is *Green* (ESG). Additionally, we have conducted a qualitative evaluation based on the yield spread a given bond trades with. Some synthetic bonds only comprise one regular bond as there are no sufficiently similar bonds. On the other hand, the biggest synthetic bond contains eight regular bonds. The average is 2.49. Information on the distribution is presented in Table 16.

Table 16 – Number of Bonds Within Synthetic Bonds								
Number of real bonds	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Number of Synthetic bonds	40	35	34	16	7	1	2	1

Table 16 - Distribution of real bonds within synthetic bonds.

The purpose is to establish a broader base of data for the liquidity measures. We have calculated the Roll measure and Amihud based on synthetic bonds. Additionally, we have made some adjustments to calculate a version of Corwin & Schultz. In the calculation of the Roll measure, we still calculate returns individually for each bond. However, we use those returns across bonds within a synthetic bond in the objects calculating covariances. Thus, on average, synthetic bonds have more observations within the rolling time window. Regarding the Amihud measure, we also use individual returns. Each daily measure is based on all bonds traded within a synthetic bond. Consequently, each daily measure, on average, is calculated based on a higher number of transactions.

For the Corwin & Schultz measure, we find the average spread between high and low prices for all bonds within a synthetic bond to create synthetic high and low prices. For instance, if a synthetic bond has three real bonds with observed high and low prices for a given day, we calculate the average spread of those three bonds for that day. Then we find a high price for the synthetic bond by taking 100 and adding half the spread, and vice-versa for the low price. Because of this, we obtain more observations for the adjusted Corwin & Schultz measure. Table 17 and Exhibits 5 and 6 summarize the results obtained based on the synthetic bonds.

Table 17 – Liquidity With Synthetic Bonds											
Roll [%]				**Corwin & Schultz** [%]				**Amihud** [%/M.NOK]			
Original		*Synthetic*		*Original*		*Synthetic*		*Original*		*Synthetic*	
Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
1.33	21.4	1.29	22.6	0.24	0.52	0.16	0.22	0.68	29.6	0.72	32.4

Table 17 - Liquidity measures with real bonds and synthetic bonds.

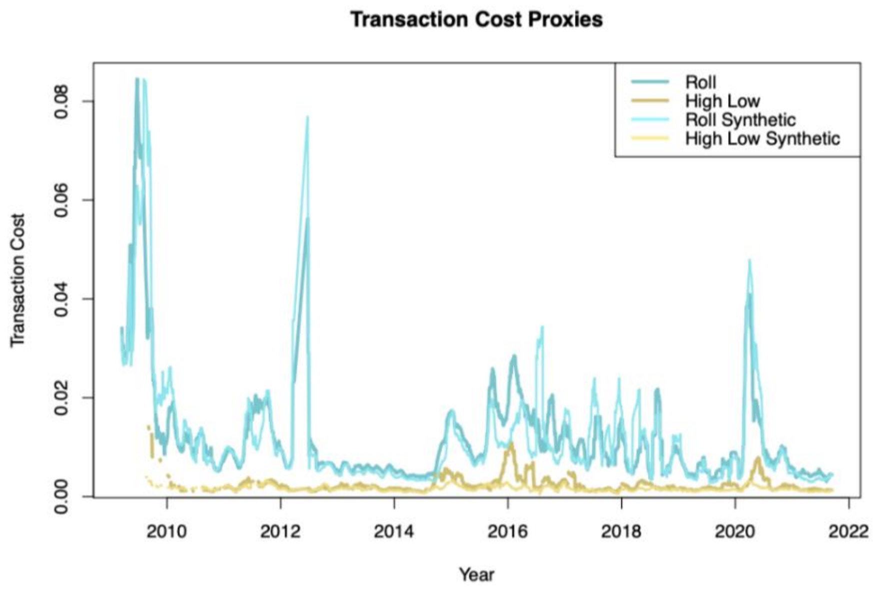

Exhibit 5 - Transaction cost estimates on Norwegian HY from 2009 to October 2021. The time series is calculated as the daily mean of transaction cost across all bonds and smoothed by taking the 30-day rolling average. We have left out some observations from 2012 for the Roll measure (both real and synthetic) as the rolling average exceeds 40%. This is only to make the plot tidy.

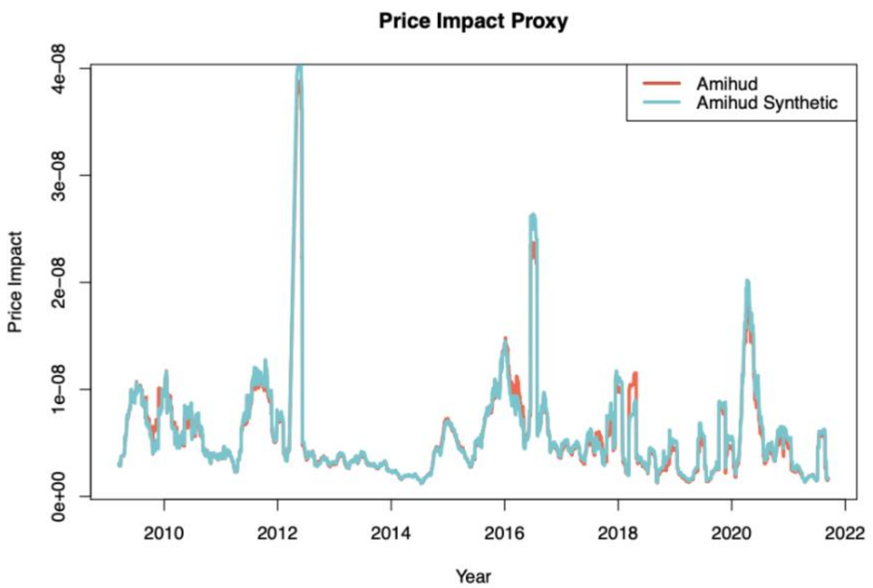

Exhibit 6 – The Amihud measure on Norwegian HY from 2009 to October 2021. The time series is calculated as the daily mean across all bonds and smoothed by taking the 30-day rolling average. As with the Roll measure, we have left out some observations from 2012 for the real and synthetic version of the Amihud measure. This is to make the plot tidy.

The establishment of synthetic bonds does not seem to capture any additional effects. Table 17 presents relatively unchanged liquidity measures. The fact that we cannot account for latent liquidity is a considerable limitation of our analysis. Investigating this aspect with sufficient investor holdings data for Norwegian HY is a highly interesting topic left for further research.

7.2 A More Sophisticated Control for Expected Loss

A good control for the expected loss component of the yield spread is missing in our regressions. The *Credit Rating* variable we employ is likely able to capture some variations driven by a company's probability of default. However, this variable does not include variations in the probability of default for each issuer at different points in time. Further, the loss given default is an equally important part of the expected loss component and a variable we do not know. Consequently, such variable is not controlled for in any of our regressions despite playing a considerable role. The inclusion of a *Loss Given Default* variable and an improvement of *Credit Rating* in a similar analysis as we have conducted could be interesting for further research.

7.3 Negative Term Premia

Our results indicate that the term premia in Norwegian HY on average has been negative during the period 2009-2021. Previous research finds that the term premium for bond markets usually is positive but can turn negative when the business environment turns sour. There are several occasions of this during the period we analyze, and it would be interesting to explore whether, and potentially how, the term premia in Norwegian HY vary in this period.

8. Appendix

8.1 Definitions of Liquidity Measures

The liquidity measures are computed for each bond individually. We separate between transaction cost measures, price impact measures, and price dispersion measures. The price and volume of a transaction $t_{i,j}$, where i index trading day, and j index trade, are represented by $p(t_{i,j})$ and $v(t_{i,j})$, respectively. We use $n(t_i)$ to refer to the observed number of trades of a financial instrument on trading day i.

8.1.1 Imputed Round-Trip Cost

The imputed round-trip cost measure assumes that when two or three trades with identical volume and ticker occur within a short period of time, they are round-trip trades. These trades are assumed to represent a pre-matched arrangement in which either one or two dealers match a buy and a sell order from a customer. Thus, the IRT measure is an alternative way of measuring the bid-ask spread of a financial instrument. The imputed round-trip cost, $irt(t_i)$, is defined as:

$$irt(t_i) = \frac{1}{b(t_i)} \sum_{w} \left(1 - \frac{min_j p_w(t_{i,j})}{max_j p_w(t_{i,j})} \right) \qquad (A.1)$$

Where w is an imputed round-trip trade which, for a given trading day i, is defined as a sequence of either two or three transactions with trade prices $p_w(t_{i,j})$ and identical volumes $v_w(t_{i,j})$. $b(t_i)$ refers to the total number of imputed round-trip trades on trading day i for a financial instrument.

8.1.2 Roll Measure

The Roll measure assumes that the price change of a financial instrument in an informationally efficient market is due to transaction cost. Thus, the covariance of consecutive trades can be used to compute a proxy for the transaction cost. The Roll measure is defined as:

$$roll(t_i) = 2 * \sqrt{-Cov\big(r(t_k), r(t_{k-1})\big)} \qquad (A.2)$$

Where the return $r(t_k)$ is defined as the percentage price change between consecutive trades on trading day k, for all k within the most recent 30 days (approximately 21 trading days). In other words, for all k that satisfy $i - k \leq 30$. For the instances where there only exists one trade within the time window from any given transaction, the roll measure cannot be computed.

8.1.3 Corwin & Schultz's High-Low Spread Estimator

The high-low spread estimator approximates the bid-ask spread by exploiting observed high and low prices. The high-low spread reflects both the bond's variance and bid-ask spread. To separate the two components, we use a two-day window where the high-low ratio is employed both on each of the two days and on the two-day period viewed as one. The bid-ask spread proxy is:

$$highlow\big(t_{i,j}\big) = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \qquad (A.3)$$

Where:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \qquad (A.4)$$

$$\beta = \sum_{j=0}^{1} \left(\log\left(\frac{H\big(t_{i+j}\big)}{L\big(t_{i+j}\big)} \right) \right)^2 \qquad (A.5)$$

$$\gamma = \left(\log\left(\frac{H\big(t_{i,i+1}\big)}{L\big(t_{i,i+1}\big)} \right) \right)^2 \qquad (A.6)$$

$H(t_i)$ is the highest price on day i and $L(t_i)$ is the lowest price. Further, the same logic applies for $H\big(t_{i,i+1}\big)$ and $L\big(t_{i,i+1}\big)$ being the highest and lowest price on two-day period i and $i + 1$, respectively.

8.1.4 Amihud Measure

The Amihud Measure quantifies the average impact of trades on a particular trading day i. It is defined as the ratio of the absolute value of the return, $r(t_{i,j}) = \frac{p(t_{i,j}) - p(t_{i,j-1})}{p(t_{i,j-1})}$, to the trading volume $v(t_{i,j})$, measured in NOK:

$$amihud(t_i) = \frac{1}{n(t_i)} \sum_{j=1}^{n(t_i)} \left(\frac{|r(t_{i,j})|}{v(t_{i,j})} \right) \qquad (A.7)$$

8.1.5 Price Dispersion Measure

The price-dispersion measure is based on the dispersion from the market's consensus and the traded price for a given security. The price dispersion measure is defined as:

$$PDM(t_i) = \sqrt{\frac{1}{\sum_{j=1}^{n(t_i)} v(t_{i,j})} \cdot \sum_{j=1}^{n(t_i)} \left(\frac{p(t_{i,j}) - m(t_i)}{m(t_i)} \right)^2 \cdot v(t_{i,j})} \qquad (A.8)$$

Where $m(t_i)$ is the market consensus. For the mean-based approach, we require at least two observations on a given day to calculate the price dispersion measure.

8.2 Robustness Checks on Monthly Averages

8.2.1 Liquidity Measures – Monthly

First, concerning section 5.2.1, the regression table with the liquidity measures as dependent variables on a monthly basis is displayed in Table 18.

Table 18 – Liquidity Measures (Monthly)

	Roll Measure (1)	IRT Measure (2)	Corwin & Schultz (3)	Amihud Measure (4)	PDM NBP (5)	PDM Avg (6)
Trading activity variables						
Volume	-0.013	-0.006***	-0.002*	-0.021***	-0.005*	-0.001***
	(0.214)	(0.000)	(0.057)	(0.003)	(0.068)	(0.008)
Days Since Last Transaction	0.044***	0.009*	-0.002	0.010**	0.016***	0.002
	(0.003)	(0.062)	(0.553)	(0.014)	(0.006)	(0.134)
Number of Trades	0.169	-0.009	0.024**	-0.284	0.089**	0.045***
	(0.751)	(0.501)	(0.042)	(0.178)	(0.036)	(0.000)
Bond Characteristics						
Coupon Rate	0.367	-0.009	-0.009	-0.076	-0.060	-0.007
	(0.465)	(0.701)	(0.475)	(0.506)	(0.371)	(0.474)
Time to Maturity	0.380***	0.095***	0.051***	0.446***	0.219***	0.039***
	(0.003)	(0.000)	(0.000)	(0.001)	(0.000)	(0.005)
Outstanding Amount	-0.457	-0.040	-0.041	-0.529**	-0.082	-0.032
	(0.186)	(0.301)	(0.196)	(0.019)	(0.449)	(0.147)
Age	-0.020	0.037*	0.021*	0.110	0.042	0.011
	(0.823)	(0.063)	(0.075)	(0.183)	(0.324)	(0.305)
Credit Rating B	-0.070	-0.005	0.127**	-0.069	0.175	0.069
	(0.769)	(0.975)	(0.039)	(0.569)	(0.556)	(0.258)
Credit Rating C	0.056	-0.012	0.154**	0.189	0.162	0.064
	(0.878)	(0.923)	(0.014)	(0.337)	(0.576)	(0.199)
Credit Rating D	0.636	0.099	0.229***	0.832*	0.363	0.126**
	(0.508)	(0.514)	(0.006)	(0.054)	(0.229)	(0.038)
Credit Rating E	7.316*	0.444*	0.301***	4.507*	1.594**	0.213**
	(0.079)	(0.078)	(0.001)	(0.083)	(0.027)	(0.048)
Credit Rating F	0.921	0.688	0.396	1.759	2.973	0.452*
	(0.465)	(0.197)	(0.142)	(0.108)	(0.191)	(0.072)
Sector Dummies	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	7,626	2,990	2,307	9,143	4,300	5,493

R2	0.033	0.301	0.252	0.025	0.259	0.189
Adj. R2	0.010	0.258	0.193	0.006	0.242	0.162
Std. Errors	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month

*P-values in parentheses (the significance levels are denoted as * = 10%, ** = 5% and *** = 1%)*

Table 18 - Regressing the Roll measure, Imputed Round Trip cost, Corwin & Schultz's High-Low Spread Estimator, Amihud measure, and the Price Dispersion measures on trading activity variables, and bond characteristics using a panel data regression with month fixed effects and robust standard errors clustered on issuer and month. Values in parentheses are the p-value. All liquidity measures are in percentage, except the Amihud measure, which is in units of percentages per one million NOK. Trading Volume is in units of million NOK and *Outstanding Amount* in billion NOK. The numerical variables are monthly averages.

8.2.2 Yield Spread - Monthly

Second, concerning section 5.2.2, the regression table with the yield spread as dependent variable on a monthly basis is displayed in Table 19.

Table 19 – Yield Spread (Monthly)

	Yield Spread						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Liquidity Measures							
Roll	3.05						28.59
	(0.172)						(0.527)
IRT		912.90***					312.51
		(0.000)					(0.184)
Corwin & Schultz			1256.34***				585.53**
			(0.000)				(0.013)
Amihud				3.12			-65.12*
				(0.342)			(0.097)
PDM NBP					406.82***		416.41***
					(0.000)		(0.000)
PDM Ave						1202.50***	197.64
						(0.000)	(0.568)
Bond Characteristics							
Coupon Rate							24.08
							(0.526)
Time to Maturity							-201.18***
							(0.000)
Outstanding Amount							0.00*
							(0.077)
Age							-12.95

							(0.716)
Credit Rating B							140.83
							(0.605)
Credit Rating C							243.72
							(0.413)
Credit Rating D							232.27
							(0.466)
Credit Rating E							877.52
							(0.383)
Credit Rating F							399.48
							(0.485)
Month FE	YES	YES	YES	YES	YES	YES	YES
Obs.	7,588	2,953	2,281	9,101	4,287	5,453	962
R2	0.058	0.335	0.313	0.057	0.285	0.256	0.644
Adj. R2	0.039	0.300	0.266	0.041	0.271	0.234	0.603
Std. Errors	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month	Issuer, Month

*P-values in parentheses (the significance levels are denoted as * = 10%, ** = 5% and *** = 1%)*

Table 19 - The table reports the result of regressing the yield spread on the Roll measure, Imputed Round Trip cost, Corwin & Schultz's High-Low Spread Estimator, Amihud measure, and the two Price Dispersion measures using a panel data regression with monthly fixed effects and robust standard errors clustered on issuer and month. In regression 7, bond characteristics are included as control variables. Values in parentheses are the p-value. All liquidity measures are in percentage, except the Amihud measure, which is in units of percentages per one million NOK. Trading Volume is in units of million NOK and *Outstanding Amount* in billion NOK. The numerical variables are monthly averages.

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