Do Corporate Bond Spreads Really Contain Illiquidity Premia?☆

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Abstract

In direct contrast to recent research, we show that the role of liquidity in the pricing of corporate bonds is limited at best. While we confirm the previously documented correlation between bond spreads and various liquidity proxies, we argue that it is due to the fact that the latter are based on measures of bond volatility and therefore - at least partially - capture credit risk. We use the Merton (1974) model of capital structure to illustrate the intimate link between bond volatility and credit spreads. Next, we introduce a simple measure of bond volatility which alone captures 53.7% of variations in credit spreads in our sample compared to 38.7% explained by seven common liquidity measures. Regressing spreads on volatility and improved controls for credit risk yields an adjusted R^2 of 69.9%. Additionally including liquidity measures only minimally augments the fit.

Key words: Structural Market Liquidity, Credit Crisis, Corporate Bonds
JEL classification: G12, G01

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1. Introduction

In the aftermath of the 2007 subprime and the subsequent sovereign debt crisis, understanding the sources of risk in credit markets matters more than ever. Motivated by recent developments in financial markets, multiple studies try to understand the drivers of corporate bond spreads, decomposing them into credit risk and illiquidity premia. Knowing which one dominates is important for investors to understand their risk exposure, can help the corporate or sovereign issuer to reduce his cost of financing and matters for any researcher modeling default risk.

Examining the relation between proxies for liquidity and credit spreads for U.S. corporate bonds, Bao et al. (2011), Friewald et al. (2012) and Dick-Nielsen et al. (2012) conclude that liquidity is important in bond pricing, which is in line with virtually all recent studies.[1] We directly contradict these studies and suggest that the role of liquidity in corporate bond markets has been substantially overstated. Specifically, we argue that common proxies for illiquidity are by construction closely related to bond volatility. Given the direct link between bond volatility and credit spreads – which we illustrate using the Merton (1974) model of credit risk – we suggest that liquidity measures to a large extent capture credit risk. While earlier studies do control for credit risk, the employed proxies are relatively poor and only reflect a portion of total credit risk, explaining why liquidity proxies have explanatory power in these analyses.

To substantiate our argument, we study the pricing of liquidity in fixed income markets using a sample of U.S.-traded corporate bonds similar to those used in previous studies and find strong empirical support for our view. First, we observe a strong pos-

[1] Also see Chen et al. (2007) and Schwarz (2010). Beber et al. (2006) and Longstaff et al. (2005) point out that default premia dominate.

itive correlation between common measures of illiquidity and bond volatility. Second, liquidity proxies that are only weakly related to bond volatility do not explain variations in credit spreads very well. Third, while we can confirm the positive relation between credit spreads and illiquidity documented in previous research, a simple measure of bond volatility clearly outperforms an aggregation of five standard liquidity measures when used to explain credit spreads. An obvious counterargument to our position is that – despite the illustrated direct link between bond spreads and volatility – the latter might in fact be an improved measure of illiquidity. To reject this argument, we use controls for credit risk which are more powerful than those used in earlier studies and show that all liquidity measures taken together fail to significantly contribute to the explanatory power of a regression model once credit risk is properly controlled for. Several robustness checks confirm our findings.

Based on the aggregate evidence, we conclude that the role of liquidity in the pricing of corporate bonds has been substantially overstated in previous research. While we do not suggest that illiquidity never matters, we reject the hypothesis that the spread on the average bond in our sample contains an economically significant illiquidity premium.

The insights of this paper are central to the debate on liquidity's place in corporate bond yields and matter most for two different research questions. First, they show how crucial it is for any study analyzing the relation between liquidity and bond spreads to appropriately control for credit risk. Second, they are important for research on structural bond pricing models. As documented by Eom et al. (2004), these tend to underpredict bond spreads. Given that they do not account for illiquidity, the existence of a large and constant liquidity premium could explain this underprediction phenomenon. Our results suggest that future research should focus on identifying overlooked factors reflecting credit risk before addressing potential liquidity effects.[2]

The remainder of this paper is organized as follows. Section 2 sets the scene by first providing an intuition why liquidity matters less in debt than in equity markets and then discussing potential limitations of earlier studies examining the role of liquidity in the corporate bond market. Section 3 proceeds with the empirical analysis. After describing data sources and sample selection in Section 3.1, Section 3.2.1 and 3.2.2 describe the measures of credit spreads and illiquidity used in this study, which are very similar or identical to those employed in related studies. Next, Section 3.2.3 illustrates the direct link between bond volatility and bond spreads using a basic structural model and introduces simple measures of bond volatility. Section 3.2.4 then outlines the way we control for credit risk in our analysis. Finally, Section 3.3 presents the results of our multivariate analysis including robustness checks. Section 4 concludes.

2. The Pricing of Liquidity

We argue that the positive relationship between measures of illiquidity and corporate bond spreads documented in previous studies is at least partly driven by credit risk. Before presenting empirical evidence supporting this conclusion in Section 3, we justify our view in the following. To do so, we first point out that the impact of illiquidity on pricing is different in debt and equity markets and then present a credit-risk-based interpretation for evidence supporting the hypothesis that liquidity matters for bond pricing presented in earlier studies.

[2] This is in line with Covitz and Downing (2007), who document that spreads on commercial papers are primarily due to credit risk and conclude that the underprediction phenomenon is due to the omission of relevant components of credit risk rather than illiquidity.

2.1. Equity versus Debt Markets

Put simply, a security's liquidity is the ease at which it can be traded. Buying or selling an illiquid security is costly, as investors face up- and downward-pressure on the security's price arising from the additional demand or supply created by the trade, respectively. Numerous studies have examined the relevance of liquidity for the pricing of both equity and fixed income securities.

A significant difference exists between an investment in most fixed-income securities and one in equity which has direct implications for the pricing of liquidity. When making an equity investment, the investor can obtain future cash flows through two channels: dividend payments and stock sales. Dividend payments often only account for a small fraction of total future cash flows from an equity investment; the largest part then comes from selling the securities. An equity investor will thus directly be affected by illiquidity as he will receive a cash flow below the reported mid-price of the security when selling it. Liquidity must therefore be priced in equity markets.

An investment in fixed income securities is fundamentally different. For example, when investing in corporate bonds with a standard fixed-rate bullet payment schedule (the ones we examine in this study), the investor exactly knows the timing and amount of future cash flows from the investment in case the issuer does not default. If the investor is not able to sell his securities at a fair price, he can thus choose to keep the investment until maturity and receive all cash-flows from his investment without having to trade his security. Only if he prefers receiving cash flows today over receiving cash flows at maturity and at the same time not sufficiently many investors exists who do not have this time preference for cash flows - which arguably was the case during the credit crunch - should an illiquid fixed income security trade at a significant discount relative to a liquid one. Results suggesting the existence of substantial illiquidity premia in bond markets even under normal market conditions have to be interpreted with caution.[3]

In summary, the outlined differences between equity and fixed income investments do not necessary imply that liquidity is not a concern for the latter. However, it means that while illiquidity must always be priced in equity markets, it can only be relevant in fixed income markets at times when a significant number of investors prefer selling their securities at a discount relative to the present value of future cash flows rather than holding them until maturity. This is in line with the arguments made in Friewald et al. (2012), Acharya et al. (2010), and Dick-Nielsen et al. (2012), amongst others. Still, our empirical results suggests that illiquidity is less relevant for bond pricing than suggested by earlier studies - even during the credit crunch.

2.2. Previous Literature

Myriad papers have been written on the existence of illiquidity premia in corporate bond spreads—of those, the most recent include Chen et al. (2007), Bao et al. (2011), Friewald et al. (2012), and Dick-Nielsen et al. (2012). While the empirical analysis of all four articles is similar to ours, our conclusions differ drastically.[4] Aside from Collin-Dufresne et al. (2001), who conclude that monthly credit spread changes are driven by neither credit risk nor liquidity, our paper is alone in finding that contemporary liquidity proxies have meagre explanatory power when properly controlling for credit risk.

Our study is most closely related to Dick-Nielsen et al. (2012) but our interpretation of results is fundamentally different. Using a similar dataset and the same set of liquidity

[3] For example, Lin et al. (2011) suggest that bonds with a high exposure to a liquidity factor yield a 4% annual excess return over a sample period of 15 years.

[4] All studies regress bond spreads (or changes in bond spreads) on proxies of illiquidity and a set of controls, just as we do.

proxies as used in this study, they document the behaviour of bond liquidity around the subprime crisis and claim that bond liquidity substantially contributes to bond spreads, especially during the subprime crisis. Amongst others, two findings support their claim. First, by regressing credit spreads on an aggregate liquidity measure and credit risk controls, they report a significant contribution of illiquidity to bond spreads. Second, they use a "paired regression", in which they match spreads of two bonds with similar maturity and issued by the same issuer in order to control for credit risk. They again show that liquidity covaries with bond spreads.

While we are able to reproduce their results, we argue that credit spreads are only marginally influenced by bond liquidity. We provide an alternative explanation for their findings. First, their controls for credit risk are mostly based on accounting data and do not fully capture credit risk. We show that using better controls reduces the marginal explanatory power of the liquidity proxies to virtually zero. Second, most of their liquidity proxies capture credit risk: They are highly correlated to simple measures of bond return volatility which we introduce in this study. As illustrated in Section 3.2.3, bond volatility is tightly linked to credit spreads. In line with this argument, our main measure of bond volatility, $VOLAADJ$ can explain variations in credit spreads better than all seven measures of liquidity used in this study.

Even if the credit risk controls used in Dick-Nielsen et al. (2012), have limitations, why do "paired regressions" that isolate variations in credit spreads within groups of bonds from the same issuer and with a similar maturity reveal a positive relation between credit spreads and liquidity proxies? One explanation for this finding consistent with our view is that even two bonds which are assigned to the same issuer can still have different credit risk, particularly for the examined time frame. There are several reasons for this to be true. First, a large part of firms in the sample underwent an M&A transaction, split off or declared bankruptcy during the sample period or briefly before. In the database, many bonds are thus assigned to an issuer which did not issue the bond in the first place but rather bought the issuing company. In many of these acquisitions the new parent does not guarantee the bonds. Second, even if there was no M&A transaction or liquidation, many bonds are issued by non-listed subsidiaries. In these cases, the credit risk of the parent company is only a good proxy of the credit risk of the bonds in the case where the parent company guarantees the issue, which is not always true. Third, even minor differences in the time to maturity can translate into differences in credit risk. For instance, Dick-Nielsen et al. (2012) assume that any difference between the yield spreads of bond A with a maturity of five years and bond B with a maturity of six years and issued by the same company can be attributed to differences in liquidity. However, given that the notional amount of bond B will be repaid one year after that of A, one can think of bond A as being senior relative to bond B. Finally, issue specific covenants can also imply differences in credit risk between two issues of the same firm. Finally, bond contracts tend to be long and complex and typically include numerous covenants which can lead to significant differences in credit risk between two bonds of the same firm.

In sum, we argue that bonds from the same issuer and with similar maturity do not necessarily have the same credit risk. Again, we point out that bond volatility can capture some of the variation in credit risk, which potentially explains the results of the Dick-Nielsen et al.'s paired regression. We support this argument by regressing bond spreads on proxies for illiquidity, volatility and credit risk after demeaning all variables, where means are computed for each combination of firm, time-to-maturity bucket, and quarter. In doing so, we take out a large part of the variation due to credit risk. We show that proxies for illiquidity now dominate our volatility measures in terms of their explanatory power. However, they can only explain a small fraction of the variation in demeaned credit spreads.

While our study is most similar to that of Dick-Nielsen et al. (2012), it also resembles those by Chen et al. (2007), Bao et al. (2011) and Friewald et al. (2012), all of which conclude that illiquidity is an important determinant of bond spreads. Except for Chen et al. (2007), all analyses rely on the same dataset for trade-level information.[5] We discuss their results in the following.

Chen et al. (2007) use a battery of liquidity measures to investigate if liquidity is priced corporate bonds, and find that it is. They employ a limited dependent variable econometric model founded on the assumption that a liquidity cost threshold exists for each bond. They find that liquidity explains 7% of the cross-sectional variation in investment-grade bonds, and 22% of variation in speculative-grade bonds. A drawback of the model acknowledged by the authors is that it requires a specification of a return-generating process for bonds. The two factors used which drive returns are the interest rate and the equity market return, both scaled by duration. A misspecification of the return process would invalidate their findings; and there is reason to believe that it is misspecified. First, Fama and French (1993) find that common factors that explain bond returns are related to maturity and default risks. Second, the authors assume the return-generating process is constant, and does not vary with the state of the economy. In a bond-return model, one can easily think of a situation where a bond's return is more sensitive to the market return on equity than usual: consider a situation where the issuing firm is near its default boundary.

[5]See Section 3.1.

Similar to Roll (1984), Bao et al. (2011) measure illiquidity as the negative covariance between lagged bond returns.[6] Clearly, this measure is directly related to bond variance and according to our argument thus partly captures credit risk. Not surprisingly, Bao et al. (2011) report that CDS spreads are by far the most powerful variable for explaining variations in their measure.[7] Furthermore, they document a strong correlation between their measure of illiquidity and the VIX index. While the authors themselves consider this finding "intriguing", it is very much in line with our view: The VIX reflects aggregate market fear and thus is likely related to credit risk. A corroboration of this view is that their measure is also strongly related to lagged stock market returns, a series shown by Campbell et al. (2008) to be particularly important for explaining distress risk, even at long horizons. While Bao et al. acknowledge that theoretical models can often be misspecified, their measure of illiquidity relies on the assumption of efficient markets, which is problematic given the abundant evidence counter to markets being efficient and displaying predictability.

Using a sample selection that is far less restrictive than ours, Friewald et al. (2012) study the relation between bond spreads and various liquidity measures including the Roll (1984) and Amihud (2002) measures used in this study, a zero-return measure similar to the zero trading measure we use, as well as the Jankowitsch et al. (2011) measure of price dispersion. They use credit ratings as their only control for credit risk to avoid an additional reduction in sample size caused by the use of alternative measures. In contrast to this and other studies, they examine changes in credit spreads and liquidity variables

[6]The Roll measure equals twice the square root of the Bao et al. measure.

[7]As documented in Table III of their study, regressing their liquidity measure on controls for bond characteristics and CDS spreads yields an R^2 of 23.07%, while regressions including the same controls and variables of market liquidity including turnover, average trade size and number of trades per month only yield R^2s of 7-8%.

over time, not their level. In brief, they conclude that liquidity matters in bond pricing, particularly during times of crisis and for bonds with a poor rating. The most important distinction between our study and theirs allowing us to draw different conclusions is their way to control for credit risk. Again, we can apply our argument that the limitation of their credit risk controls benefits any liquidity measure which partly captures credit risk. In line with our view, Friewald et al. (2012) document that measures of trading activity – which are clearly less related to bond volatility than the previously named liquidity measures they employ – have relatively low explanatory power. This is in line with our results and Dick-Nielsen et al. (2012), who exlcude the turnover and zero trading measure from their core analyses for their lack of explanatory power.

3. Empirical Analysis

Our analysis is comparable to the studies by Bao et al. (2011), Dick-Nielsen et al. (2012) and Friewald et al. (2012) in terms of data sources, sample selection, and research question. We examine a similar set of proxies for bond liquidity to test the relation between liquidity and bond spreads. As documented in the following, we obtain results that are comparable to theirs and appear to support the hypothesis that in addition to credit risk, liquidity explains variation in bond spreads. We then extend the previous analysis by proposing a simple measure of bond volatility, as well as largely improved measures of credit risk similar to those introduced in Campbell et al. (2008) for default prediction. Including these in the analysis substantially increases model fit and at the same time decreases the statistical and economic significance of all liquidity proxies. Observing that almost all commonly used liquidity proxies are highly related to bond price volatility, we argue that at least to some extent common liquidity proxies capture credit risk, not illiquidity.

3.1. Data Sources and Sample Selection

The primary dataset used in the analysis is the Trade Reporting and Compliance Engine (TRACE). The Financial Industry Regulatory Agency (FINRA) introduced TRACE in July 2002 in order to increase the transparency of the corporate bond market. FINRA members are required to report details on their over-the-counter transactions through TRACE. The third phase of TRACE was launched in October 2004; from this date, information about trades in almost all bonds is accessible via the engine. Given that we use quarterly observations in our analysis, we consider the time period starting in January 2005. Our sample periods ends on June 30th 2011. TRACE provides us with transaction data including yield to maturity, volume, price, as well as a set of reporting related variables needed to clean the dataset from erroneous entries.[8]

In addition, we obtain security level data from the Mergent Fixed Income Securities Database (FISD). Variables downloaded from FISD's bond issue file include bond type, coupon type, amount outstanding, and dummy variables indicating sinking funds, convertible bonds, and put and call features; their ratings file provides us with issue specific ratings by S&P, Moody's and Fitch. We use constant maturity treasury rates from the Federal Reserve's H15 report as the risk-free rate.

We complement the bond dataset with stock market and accounting data by matching it to the CRSP-Compustat databases. These provide us with all input variables needed to construct our credit risk controls. CRSP variables include daily stock returns and monthly data on stock price, stock return and shares outstanding for all bond issuers, as

[8]For details, see Dick-Nielsen (2009).

well as the monthly return and market capitalization of the S&P500 index. Compustat data includes the quarterly items total assets, cash and short-term investments, total liabilities, net income and equity book values.

Our initial sample comprises all fixed-rate corporate bonds included in both the TRACE and FISD databases which are labelled corporate debentures, medium term note or retail note by FISD and for which trading data is available during the sample period. The initial sample comprises 34,285 debt issues. We exclude issues with sinking fund provisions, without rating data, as well as all convertible, putable and callable securities and are left with 12,185 bond issues.

In a next step, we eliminate erroneous transaction data from the TRACE database using the three step procedure described in Dick-Nielsen (2009). Furthermore, we delete all transactions for bond-days without rating data, with a volume of less than $100,000, trades for which the issue's time to maturity is less than 1 month or more than 30 years, as well as trades for which the yields reported in TRACE deviate significantly from yields computed manually using bond parameters obtained from TRACE and FISD.[9]

As detailed in the following paragraphs, our sample further reduces when aggregating the trade data to quarterly observations, calculating the liquidity measures, and matching the dataset with CRSP and Compustat data. Our final sample includes 19,898 bond-quarter observations for 2,566 bond issues and 382 firms. As a comparison, the sample used by Dick-Nielsen et al. comprises 14,464 bond-quarter observations for 2,224 bond issues and 380 issuers. For their sample period, our sample includes 14,105 bond-quarter observations for 2,034 bond issues and 364 issuers. We consider these differences as minor and assume that they are at least partly due to the fact that we rely on FISD to obtain

[9] More specifically, we discard trades for which one yield is larger than 1.05 times the other.

information on bond characteristics whereas Dick-Nielsen et al. use Bloomberg.

In summary, our sample selection closely resembles that of Dick-Nielsen et al. (2012) and is significantly more restrictive than that of Friewald et al. (2012).[10] While the sample of the latter represents a substantially larger portion of all corporate bond transactions, this comes at the cost of increasing the heterogeneity of the sample. For example, by not excluding bonds with sinking fund provisions, put or call features, or conversion options, they ignore various factors which can be expected to have an important impact on yield spreads. Even if we chose a more restrictive sample selection, the insights generated in this article are important for the pricing of bonds not included our sample, too.

3.2. Construction of Variables

We construct credit spreads and measures of illiquidity on a quarterly basis following Dick-Nielsen et al. (2012). Noteworthy deviations from their approach are outlined and justified subsequently. Our set of controls for credit risk differs substantially from theirs as described below.

3.2.1. Credit Spreads and Rating

On a transaction level, we compute credit spreads as the difference between the reported yield to maturity and the maturity-matched risk-free rate. The yield curve required for this is constructed by interpolating the daily rates on constant maturity treasuries using cubic splines. To reduce the effect of outliers in the final analysis, we follow Dick-Nielsen et al. (2012) and winsorize transaction-level credit spreads at their

[10]The sample in Bao et al. (2011) is even more restrictive than ours and Chen et al. (2007) use a different data set.

0.5th and 99.5th percentile. In other words, we set the lower and and upper 0.5% of the credit spread distribution equal to its 0.5th and 99.5th percentile.

We then aggregate transaction-level credit spreads on a quarterly basis as follows: After discarding all trades made in the first two months of a quarter, we compute the end of quarter credit spread as the average spread of the last day for which at least one trade is reported in a quarter. The quarterly credit rating is the S&P credit rating as of that day. If no S&P rating is available, we use the Moody's rating and if there is no rating available from Moody's, we use the Fitch rating.

Table 1 displays descriptive statistics of the distribution of credit spreads (in percent) for different ratings.

[Table 1 about here.]

Not surprisingly, credit spreads decrease in rating and the largest difference can be observed between spreads of BBB bonds and speculative grade bonds.

3.2.2. Measuring Liquidity

For the sake of comparability, we rely on the same measures of liquidity as Dick-Nielsen et al. (2012). Friewald et al. (2012) employ a subset of these (or similar) measures and additionally include the Jankowitsch et al. (2011) measure of price dispersion which by construction is correlated to bond volatility. The illiquidity measure used in Bao et al. (2011) is tightly linked to the Roll (1984) measure included in this study.[11] In brief, we use measures that are identical to or close to those used in comparable studies.

Following Dick-Nielsen et al. (2012), we use a slightly modified version of the Amihud (2002) measure of illiquidity. The measure quantifies the market depth, i.e. how strongly

[11] The Roll measure equals twice the square root of the Bao et al. measure.

the market reacts given a certain transaction size, by relating return to trading volume on a daily basis as follows:

$$Amihud_d = \frac{1}{N_d} \sum_{j=1}^{N_d} \frac{|r_j|}{Q_j}, \tag{1}$$

where N_d is the number of trades on day d, r_j is the bond return observed between the two subsequent transactions j and $j-1$ and Q_j is the transaction volume. The daily measure can only be computed for days with at least two transactions. We compute the quarterly measure *Amihud* as the median of all daily measures in a quarter.

Roll (1984) shows that in an efficient market the bid-ask spread can be measured as

$$Roll_d = 2\sqrt{-cov\left(R_i, R_{i-1}\right)}, \tag{2}$$

where $cov\left(R_i, R_{i-1}\right)$ is the negative first-order serial covariance of returns. We compute a daily Roll measure on days with at least one transaction using data for all trades reported for the days $d-21$ to d. If there are less than five trades reported for the 21 day window or if the serial covariance is positive, we discard the observation. We aggregate the daily measure to a quarterly one (*Roll*) by computing the median of all daily values observed in a quarter.

Feldhuetter (2011) derives an alternative measure of the bid-ask spread based on the observation of "imputed roundtrip trades" (IRT). He argues that when the same number of bonds of an issue is traded two or three times within a short period it is likely part of an aggregate transaction in which a bond dealer matches a buyer and seller. If there is one intermediary dealer, two trades will take place: One between buyer and dealer and one between seller and dealer. If there are two dealers, three deals will be executed. We define an imputed round trip as a set of two or three trades of the same number of bonds observed for the same issue and the same day and compute the imputed roundtrip cost as

$$IRC^* = \frac{P_{max} - P_{min}}{P_{max}}, \tag{3}$$

where P_{max} and P_{min} are the highest and the lowest price observed for an IRT. We calculate a daily measure as the average IRC^* for each day with at least one IRT and aggregate the daily measure to a quarterly one (IRC) by computing the average of all daily values of that quarter.

The fourth and fifth measure capture trading activity. $ZeroTrading$ equals the percentage of trading days in a quarter during which no trades were observed for a bond. Bond turnover is defined as

$$Turnover = \frac{TradingVolume_q}{AmountOutstanding}. \tag{4}$$

In addition to the above, we calculate the measures σ_{Amihud} and σ_{IRC} as the standard deviation of the daily Amihud and IRC measures observed for a quarter, respectively. Dick-Nielsen et al. (2012) argue that investors may not only price current liquidity but also account for potential changes in liquidity over time and use the two measures to capture this. We winsorize the right tail of all seven measures by setting the upper 0.5 percent of each distribution equal to the 99.5 percentile.

Finally, we aggregate some of the above liquidity measures. Given the high correlation between liquidity measures as well as between liquidity and volatility measures, this allows reducing problems of multicolinearity. Dick-Nielsen et al. (2012) use principal component analysis to identify $Amihud$, IRC, σ_{Amihud} and σ_{IRC} as the most important measures of illiquidity and aggregate them in a single variable λ_{DN} by simply computing the sum of the measures standardized to a common scale. Each measure thus enters with an equal weight. For our sample, we observe that the *Roll* measure explains a significant portion of variation in credit spreads.[12] We therefore slightly depart from their approach and define an aggregate measure λ as the sum of all five standardized measures.[13]

Table 2 shows descriptive sample statistics for all liquidity measures. Chen et al. (2007) , Acharya et al. (2010), and Friewald et al. (2012) argue that illiquidity premia are more important for bonds with high credit risk. In contrast, Bao et al. (2011) report that their proxy of illiquidity is most powerful for explaining changes in bond yields for bonds rated A or better. To understand whether the components of credit spreads are different for subsampple of bonds with a high and low rating, we report summary statistics and multivariate results for the aggregate sample, as well as subsamples of bond-quarters with a high and a low rating throughout our study.

In line with previous research, we observe that the core measures of illiquidity are substantially higher for bond quarters with a low rating than for those with a rating of A or higher. The percentage of days without trades, $ZeroTrading$ is significantly higher for the former. In part, this may be due to the fact that our sample does not include low volume trades, which likely occur more frequently for some risky bonds. In contrast, the $Turnover$ measure does not support the hypothesis that bonds in higher rating classes are more liquid – it only differs marginally between the two subsamples. While good

[12]Specifically, regressing credit spreads on all seven measures (only λ_{DN} or only λ) yields an adjusted R^2 of 38.7% (30.0% or 34.0%).

[13]A measure is standardized by first subtracting the measure's average and then dividing by its standard deviation for the pooled sample.

arguments why liquidity may be higher in bonds with a higher rating exist, the overall picture is also very much in line with our view that illiquidity proxies capture credit risk.

[Table 2 about here.]

Table 3 displays correlations between all liquidity measures. It offers two important insights. First, some liquidity measures exhibit a high correlation with each other, which indicates potential multicolinearity problems that we can confirm in a multivariate context.[14] Summarizing the most relevant proxies in an aggregate measure is therefore important. Second, λ and λ_{DN} are highly correlated. Furthermore, the correlations between our main liquidity measure λ and its constituents are high and very similar to those between λ_{DN} and its constituents (excluding the Roll measure which λ incorporates while λ_{DN} doesn't, of course). Our slight deviation in the definition of λ can thus be expected not to significantly decrease the comparability of our results and those of Dick-Nielsen et al. (2012).

[Table 3 about here.]

Figure 1 shows the quarterly averages of all nine liquidity measures. In line with our claim that the liquidity measures which can best explain variations in credit spreads (those that we bundle in λ) are in fact related to credit risk, these measures spike during the financial crisis of 2008, while the simple measures $Turnover$ and $ZeroTrading$ do not exhibit this pattern. In contrast, the measures of bond volatility discussed in Section 3.2.3 exhibit a highly similar pattern, as shown in Figure 3.

[Figure 1 about here.]

[14] We do not report these results but they are available upon request.

3.2.3. Bond Volatility

Our view that the role of illiquidity in corporate bond markets has been substantially overstated in recent research is based on the observation that common liquidity proxies are closely related to bond volatility which in turn captures credit risk. In the following, we first illustrate the tight link between bond volatility and credit spreads using a simple structural model for bond pricing. We then outline how we measure bond volatility in this study.

The Link between Bond Volatility and Spreads

In the following, we derive the link between bond volatility and spreads for a simple structural model of bond pricing. We do not use the obtained analytical solutions in our empirical analysis but merely use the framework to illustrate how closely related the two measures are.

Assuming a structural model of bond pricing as the one proposed by Merton (1974), the probability that a firm defaults on its debt is a function of its asset risk. In such a framework, equity risk is closely related to asset risk; one way to establish a relationship between equity and debt is by using the "optimal hedge equation" known from delta-hedging.[15]

In line with the Merton (1974) model, the optimal hedge equation describes the relationship between equity and firm risk σ_E and σ_V as

$$\sigma_V = \frac{E}{VN\left(d_1\right)}\sigma_E, \tag{5}$$

where $\frac{V}{E}$ measures leverage and $N\left(d_1\right)$ the sensitivity of option values to changes in the

[15] We assume zero dividend payouts for the sake of simplicity.

underlying. It is below 0.5 for out of the money call options – corresponding to firms in financial distress – and approaches one as the moneyness increases. Consistent with the direct link between equity and asset risk, and asset and default risk, Campbell and Taksler (2003) demonstrate that idiosyncratic equity volatility explains as much variation in credit spreads as do credit ratings.

The relation between debt volatility σ_D and asset volatility can be established analogously as

$$\sigma_V = \frac{D}{VN\left(-d_1\right)}\sigma_D. \tag{6}$$

In the following, we use this relation to illustrate the link between debt volatility and bond spreads, which can be computed as a function of asset volatility σ_V in the Merton model.

According to the model, a company is financed with equity and a single zero coupon bond of value D:

$$D = Fe^{-yT}, \tag{7}$$

where F is the face value of debt, T the time to debt maturity and y the yield to maturity. Credit spreads can thus be calculated as

$$s = -\frac{ln\left(D/F\right)}{T} - r, \tag{8}$$

where r is the risk free rate. Furthermore, the Merton model assumes that debt is a combination of a risk-free bond with face value F and a short put option on firm assets:

$$D = Fe^{-rT} - P, \tag{9}$$

with

$$P = Fe^{-rT}N\left(-d_2\right) - VN\left(-d_1\right), \tag{10}$$

where

$$d_1 = \frac{ln\left(\frac{V}{F}\right) + (r + .5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{11}$$

and

$$d_2 = d_1 - \sigma_V\sqrt{T}. \tag{12}$$

Taken together,

$$s = -\frac{1}{T}ln\left(e^{-rT}N\left(d_2\right) + \frac{V}{F}N\left(-d_1\right)\right) - r. \tag{13}$$

Based on equations 6 and 11-13, we plot the relation between bond volatility and spreads for different levels of leverage in Figure 2.

[Figure 2 about here.]

The solid, dashed and dotted line represents a ratio of face value to firm value equal to 0.05, 0.25 and 0.95, representing the case of a firm with low leverage, normal leverage and a firm close to financial distress, respectively. To create the graph, we vary σ_V between 0 and 150%. Based on this range, the maximum bond volatility of low leverage firms is lower than that of high leverage firms explaining why functions cover a smaller range of σ_D for lower leverage. The graph illustrates how closely credit spreads are linked to bond volatility. This is intuitive, as bond volatility depends on leverage (indicating the proximity to financial distress) and firm risk. In the given framework, not only is the relation monotone, it also is close to linear for realistic parameter values. As shown in

Figure 4, this is in line with the relation actually observed for our sample. The shape of the function is not significantly affected by changing other parameters such as T.

Bond volatility is thus intimately linked to credit risk. Any measure of illiquidity which is related to the variance in bond returns will therefore capture credit risk, too. In order to assess whether this can explain the significant relationship between proxies for bond liquidity and credit spreads documented in earlier studies, we subsequently propose several proxies of bond volatility which we use in our empirical analysis.

Measuring Bond Volatility

The challenge in calculating the volatility of returns on corporate bonds are the low number of transactions observed for a large part of our sample. Of course, all liquidity measures used in this context face the same problem of limited data availability. We use four simple measures of bond volatility in this study and compute these measures on a quarterly basis for each bond issue.

$VOLA$ is defined as the standard deviation of all bond returns in a quarter. $RANGE$ is the difference between the maximum price and the minimum price observed during a quarter scaled by the maximum price. Both measures ignore that trades are not observed at the same frequency for all bonds. One way to account for different trading frequencies is via the square root of time rule. For example, to compute comparable annualized standard deviations using monthly and daily return data, one has to multiply the original standard deviation with the square root of 12 and 252, respectively (assuming 252 trading days per year). We use the square root of time rule to adjust both $VOLA$ and $RANGE$ for differences in the trading frequency and calculate them as

$$VOLAADJ_q = VOLA\sqrt{4 \times N_q} \tag{14}$$

and

$$RANGEADJ_q = RANGE\sqrt{4 \times N_q} \tag{15}$$

where N_q equals the number of trades reported in quarter q. For example, if there is only one observation per quarter, we multiply with $\sqrt{4}$ to obtain the annualized standard deviation. If there are 63 observations per quarter, we multiply with $\sqrt{4 \times 63} = \sqrt{252}$, which resembles the case of daily observations.

Table 4 shows descriptive sample statistics for the four volatility measures. All four measures are substantially higher for bond quarters with a low rating than for bond quarters with a high rating. Of course, this is in line with our argument that bond volatility is tightly linked to credit risk.

[Table 4 about here.]

Table 5 displays correlations between all volatility measures. Several measures exhibit high correlations to one another. In order to avoid multicollinearity problems in the multivariate analysis, we therefore restrict our later analysis to the measure $VOLAADJ$. Relative to the two range measures, the volatility measures capture more information. The adjusted measure can be regarded as more precise as it corrects for differences in trading frequency. Not only is the chosen measure therefore the most intuitively appealing one, it also proves to outperform the other measures (and any set of liquidity measures) when used to explain variations in credit spreads.

[Table 5 about here.]

Figure 3 shows the evolution of all four measures over time. Clearly, the time series of the measures are correlated with those of the measures of bond illiquidity excluding those of trading activity (zero trading days and turnover), displayed in Figure 1.

[Figure 3 about here.]

To further demonstrate the direct link between credit spreads and bond volatility, Figure 4 plots the relation between the two observed in our sample. It shows median (solid line) and average (dashed line) values of both variables for subsamples formed according to the $VOLAADJ$ decile. It is strictly monotonic and almost linear, which is in line with the relation implied by the Merton (1974) model discussed in Section 3.2.3.

[Figure 4 about here.]

Finally, Figure 5 plots the relation between bond volatility and each of the nine liquidity measures found in our sample, showing median values of both variables for each subsample formed according to the $VOLAADJ$ decile. The strong positive correlation between the core liquidity measures and bond volatility, as well as the is in line with our argumentation.

[Figure 5 about here.]

3.2.4. Controlling for credit risk

Searching for the best predictors of default risk, Campbell et al. (2008) find that market-based measures tend to outperform book-value-based measures. We therefore depart from Dick-Nielsen et al. (2012) who use the set of accounting measures proposed in Blume et al. (1998) and use the variables identified in Campbell et al. (2008) as best predictors of default.[16] More specifically, we include measures of equity volatility

[16] Also see Campbell et al. (2010).

($SIGMA$), equity outperformance ($EXRETAVG$), relative firm size ($RSIZE$), stock price truncated at \$15 ($PRICE$), profitability ($NIMTAAVG$), leverage ($TLMTA$), and firm-level liquidity ($CASH$) to control for credit risk. In contrast to Campbell et al., we compute all measures on a daily basis using the information available one day prior to the observation of a credit spread. The intuition underlying these measures is as follows.

A larger magnitude of equity volatility, through its relationship to asset volatility via the Merton model, will capture a greater likelihood of default. Equity outperformance is the return on a stock in excess of the market. This measure is averaged with a geometrically-declining weight. The idea is that a firm close to bankruptcy should underperform the market as its default event becomes more probable. Smaller firms are less equipped to secure temporary financing to stave off default; hence, we control for their size relative to the aggregate market. Distressed stocks typically have low stock prices, a reflection of their decline. On top of these measures, standard accounting-based metrics for firm profitability, leverage, and cash holdings are included, but market-based estimates for equity are used in place of book values. Profitability, too, is averaged with geometrically-declining weights, as distressed stocks typically show back-to-back earnings losses prior to default.

Table 6 shows descriptive sample statistics for all credit risk controls. Some of them are intuitive. Amongst others, companies with low-rated bonds have less cash, are smaller, exhibit low stock prices more frequently, have a lower median market-to-book ratio and more volatile equity returns. Others are less intuitive. For instance, companies with low-rated bonds have higher excess returns (which can be explained with a size and market-to-book effect) and the evidence on both leverage and profitability is mixed.

[Table 6 about here.]

Concluding the section on the construction of our explanatory variables, Table 7 displays correlations between credit spreads CS, our main measures of bond illiquidity (λ) and volatility ($VOLAADJ$) as well as all proxies for credit risk proposed by Campbell et al. (2008) and computed on a daily basis in this study. In line with our argumentation, we note that the correlation between credit spreads and bond volatility is stronger than that between credit spreads and liquidity. In addition, we observe a strong correlation between our liquidity measure and bond volatility.

[Table 7 about here.]

3.3. Multivariate Results

In this study we argue that the positive relation between credit spreads and liquidity measures documented in previous research has to be interpreted with caution, as liquidity measures are related to bond volatility and therefore partly capture credit risk. The core findings supporting our view are summarized in Table 8, showing estimates of regressions of credit spreads on measures of bond liquidity, credit risk, and bond volatility.[17] Given that some issuers have multiple bonds outstanding, we follow Petersen (2009) and adjust our standard errors for two-way (firm-quarter) clustering. Column (1) reports results for the regression including only our liquidity measure λ. In line with the studies of Dick-Nielsen et al. (2012), Friewald et al. (2012) and Bao et al. (2011), amongst others, we find that illiquidity is positively related to credit spreads. λ explains a significant

[17] We do not include additional control variables such as time to maturity or the slope of the yield curve as their explanatory power is marginal. Ignoring them gives an undistorted view of how the variables of interest relate to credit spreads.

portion of the variations in credit spreads, the adjusted R^2 equals 34.0%. Column (2) contains information for the model only including bond volatility ($VOLAADJ$) which alone explains 53.7% of the variation in quarterly credit spreads. Adding our liquidity measure λ to the model (Column (3)) does not increase the fit significantly. The most obvious counterargument to our view that λ captures credit risk given its correlation to bond volatility is that bond volatility itself measures liquidity risk. Even though we regard the link between credit risk and bond volatility as more direct than that between credit spreads and λ, and despite the better fit of the bond volatility measure, we can not conclude whether credit risk, illiquidity or both drive credit spreads only by looking at $VOLAADJ$ and λ. We therefore now turn to our set of controls for credit risk. As outlined in Section 3.2.4, these have been identified by Campbell et al. (2008) as the most powerful predictors of corporate default and have several advantages over the credit controls used earlier research. Given that these variables do not contain bond market information, they are not directly linked to the liquidity of the bonds in the sample. Any covaration with credit spreads can therefore be attributed to credit risk. The model including only these credit controls (Column 4) yields and adjusted R^2 of 64.5% and except for the lack of significance of leverage and cash holdings, all variables enter the regression as expected. While adding λ increases the fit by only 2.8%, including $VOLAADJ$ adds another 5.4% to the model's explanatory power. Even though the coefficient of λ is still significant and positive in the model including all variables, its marginal explanatory power is minimal.

[Table 8 about here.]

To deepen our understanding how the previously mentioned firm-quarter clustering affects regression results, we additionally run the same set of regressions displayed in Table 8 after aggregating each variable on firm-level by calculating averages for each firm-quarter. Doing so might strengthen the explanatory power of our credit risk controls as they do not vary significantly within each cluster. Table 9 reports results for firm-level regressions. Relative to the issue level regressions, we do not observe an increase in the explanatory power of our credit risk controls (Column 3). However, the power of our measure for bond volatility $VOLAADJ$ increases significantly (Column 2) and completely eliminates the marginal explanatory power of λ (Column 4), whose coefficient is no longer significant. The fit of the best model increases slightly when using firm-level data.

[Table 9 about here.]

In order to illustrate how the choice of a credit risk proxy which only partly captures default risk can impact the result in favor of the illiquidity measure λ, we report results for regressions of credit spreads on λ, $VOLAADJ$, rating dummies (one for each rating class), as well as our credit risk controls in Table 10. Again, standard errors are adjusted for two-way firm-quarter clustering. Rating dummies alone explain only 25.3% in the variation of credit spreads; adding our liquidity measure λ augments the fit to 44.2% suggesting that illiquidity is a powerful explantory variable of credit spreads. However, our simple measure of bond volatility, $VOLAADJ$, outperforms λ in this setting, boosting the adjusted R^2 to 60.8%. This number remains virtually unchanged when adding λ to the regression including $VOLAADJ$ and rating dummies. Also including our controls for credit risk augments the fit to 72.7%.

[Table 10 about here.]

Multiple studies argue that the impact of liquidity on bond spreads varies between rating classes. Chen et al. (2007) , Acharya et al. (2010), and Friewald et al. (2012) argue that illiquidity premia matter most for bonds with high credit risk. In contrast, Bao et al. (2011) report that their proxy of illiquidity is most powerful for explaining changes in bond yields for bonds rated A or better. The underprediction of bond spreads by structural models documented by Eom et al. (2004) could be explained by the existence of an illiquidity premium that is highest for bonds with a good rating. To understand whether the effect of liquidity on bond yields indeed depends on the rating, we report results of regressions identical to those reported in Table 8 but estimated for rating subsamples in Table 11. The upper two panels split the sample into bond-quarters with a rating of A and above and those with a rating below A. The third panel reports regression estimates for a subsample of the bonds included in the second panel, namely those with a speculative grade rating.

Indeed, we observe several differences between these subsamples. Looking at the explanatory power of the models including only λ (Column (1))suggest that illiquidity matters most for bonds with a low rating: The adjusted R^2 for these bonds (40.9%) is significantly higher than that of bonds with a high rating (22.7%). In line with our results for the aggregate sample documented previously, Column (2) and (3) reveal that almost all explanatory power can be attributed to bond volatility. Interestingly, this effect is strongest for the subsample of speculative grade bonds: the contribution of λ to the fit of the regression is virtually equal to zero once $VOLAADJ$ is included, which becomes clear when comparing the adjusted R^2s of Column (2) and (3) and those of

Column (5) and (6).

So far we have been cautious with interpreting our results as evidence that liquidity never plays a significant role in corporate bond pricing, merely suggesting that previous research substantially overstated its importance. This view left space for a potential relevance of liquidity outside our sample which we - in line with other studies - constructed relatively restrictively on purpose. Findings in earlier studies including Friewald et al. (2012) indeed suggest that liquidity matters most for risky bonds - some of which have been excluded from our sample. However, the aggregate evidence presented in Table 11 suggests that the explanatory power of credit risk is even higher for bonds with a low rating and makes us even more confident that our conclusion that liquidity plays a limited role in bond pricing can be generalized.

[Table 11 about here.]

In summary, we interpret the aggregate findings as strong support for our hypothesis that the role of illquidity for the pricing of corporate bonds is limited at best – at least for our sample. It is important to recall that our sample selection follows Dick-Nielsen et al. (2012) and is relatively restrictive. Various studies, including that Friewald et al. (2012), argue that illiquidity matters most for bonds with poor credit quality and in times of financial distress. Of course, it is therefore possible that illiquidity is more important for observations excluded from our sample. Still, our findings strongly suggest that the importance of liquidity in corporate bond markets has been substantially overstated in previous research. Any related study can only draw robust conclusions when properly controlling for credit risk.

4. Conclusion

The 2007 subprime crisis and the subsequent sovereign debt crisis make clear how crucial an understanding of forces that drive credit markets is for market participants and academics. Motivated by recent developments in credit markets, various studies examine the importance of illiquidity for the pricing of corporate bonds. In summary, these studies document a positive relationship between credit spreads and measures of bond illiquidity and conclude that liquidity plays an important role in bond pricing.

Relying on a similar data set, we revisit these analyses and come up with an entirely different interpretation. Specifically, we argue that common proxies for illiquidity are by construction tightly linked to bond volatility. Given the direct link between bond volatility and credit spreads – which we illustrate using a simple structural model of credit risk – we suggest that liquidity measures to a large extent capture credit risk. While earlier studies do control for credit risk, the employed proxies are relatively poor and only reflect a portion of total credit risk, explaining why liquidity proxies have explanatory power in these analyses. Several empirical findings offer strong support for our view.

First, we observe a strong positive correlation between common measures of illiquidity and bond volatility. Second, liquidity proxies that are only weakly related to bond volatility do not explain variations in credit spreads very well. Third, while we can confirm a positive relation between credit spreads and illiquidity, a simple measure of bond volatility clearly outperforms an aggregation of five standard liquidity measures when used to explain credit spreads. An obvious counterargument to our position is that – despite the illustrated direct link between bond spreads and volatility – the latter might in fact be an improved measure of illiquidity. To reject this argument, we use controls for credit risk which are significantly more powerful than those used in earlier studies and show that all liquidity measures taken together fail to significantly contribute to the explanatory power of a regression model once credit risk is properly controlled for.

In sum, our findings offer strong support for our view that the role of illiquidity in corporate bond markets has been substantially overstated in recent research. In turn, the role of credit risk has been underestimated. Our findings are most important for future research in two main areas. First, they show that it is crucial for any study analyzing the role of liquidity in credit markets to appropriately control for credit risk. In this study, we suggest using the daily versions of the set of credit controls initially proposed by Campbell et al. (2008). Second, research on structural bond pricing models should aim at identifying overlooked factors reflecting credit risk before attempting to incorporate liquidity risk.

Despite the strong empirical evidence presented in this study, we do not conclude that liquidity never plays a role in bond pricing. It is well possible that liquidity does matter for specific securities which may not even be represented in our sample or during specific, limited time frames. However, in light of our findings, we reject the hypothesis that a large and constant liquidity premium exists for the broad cross-section of corporate bonds.

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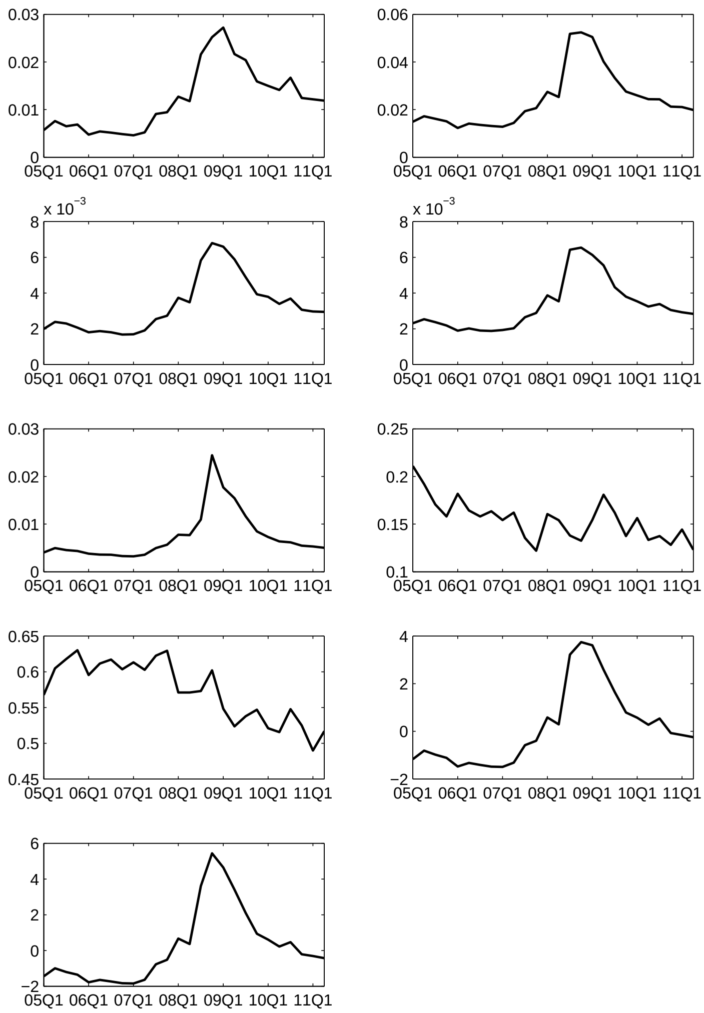

Figure 1: *Average bond-level liquidity proxies over time.*
Displayed are the time series of quarterly average bond liquidity measures, Amihud, σ_{Amihud}, IRC, σ_{IRC}, Roll, Turnover, ZeroTrading, λ_{DN}, λ (from upper left to lower right).

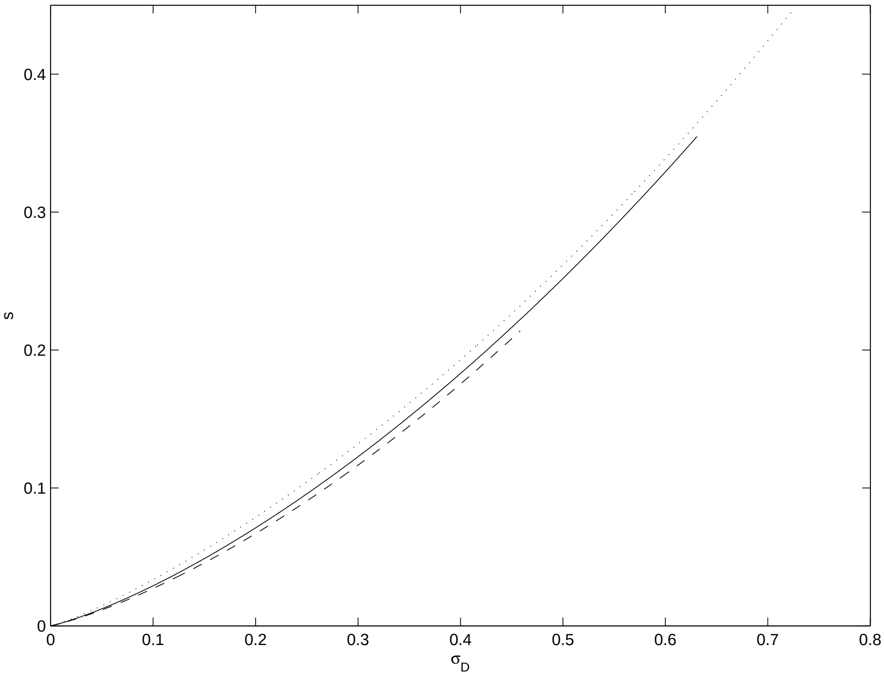

Figure 2: *Bond spreads as a function of bond volatility.*
This graph shows the relation between bond volatility σ_D and bond spreads s as implied by the Merton (1974) model for three different levels of leverage. σ_D is computed as a function of σ_V, which we vary from 0 to 150%. $T = 5$, $r = 0.05$, $F/V = 0.05$, 0.35, 0.95 (solid, dashed and dotted lines, respectively).

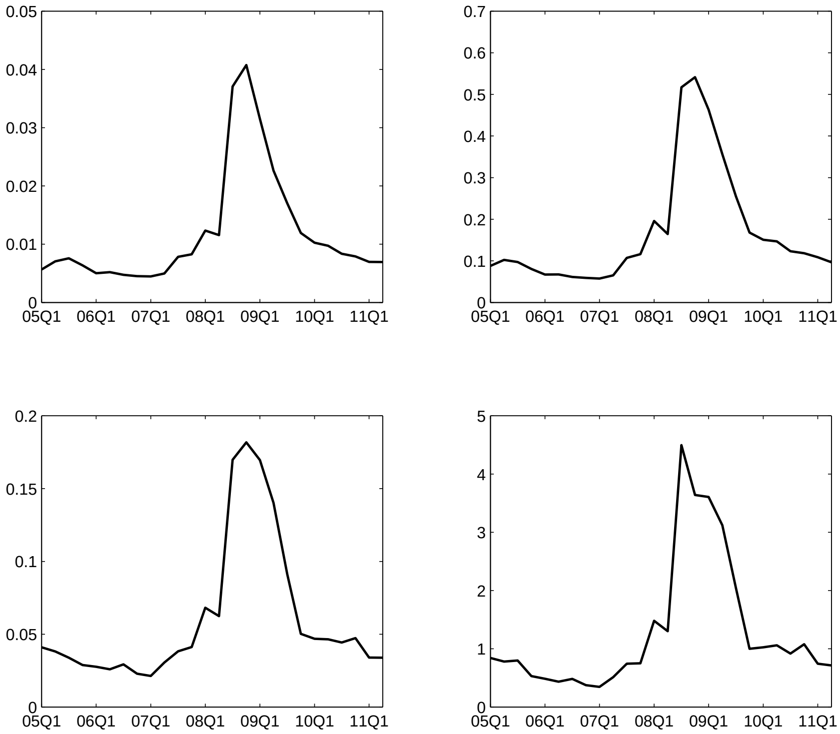

Figure 3: *Average bond volatility over time.*
Displayed are the time series of the four bond volatility measures VOLA, VOLAADJ, RANGE, and RANGEADJ. The averages are computed per quarter based on firm-level variables.

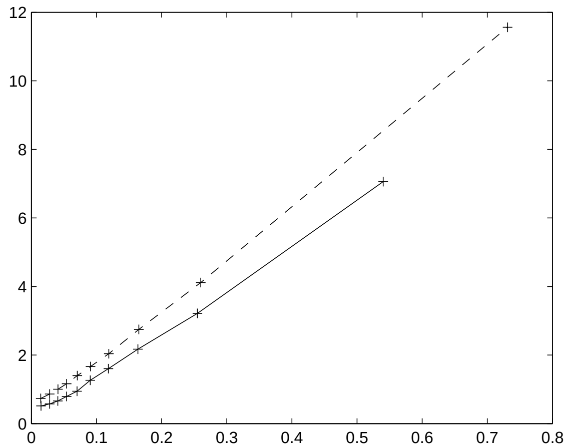

Figure 4: *Credit spreads and bond volatility.*
This graph plots median (solid line) and average (dashed line) values of both variables for each subsample formed according to the $VOLAADJ$ decile.

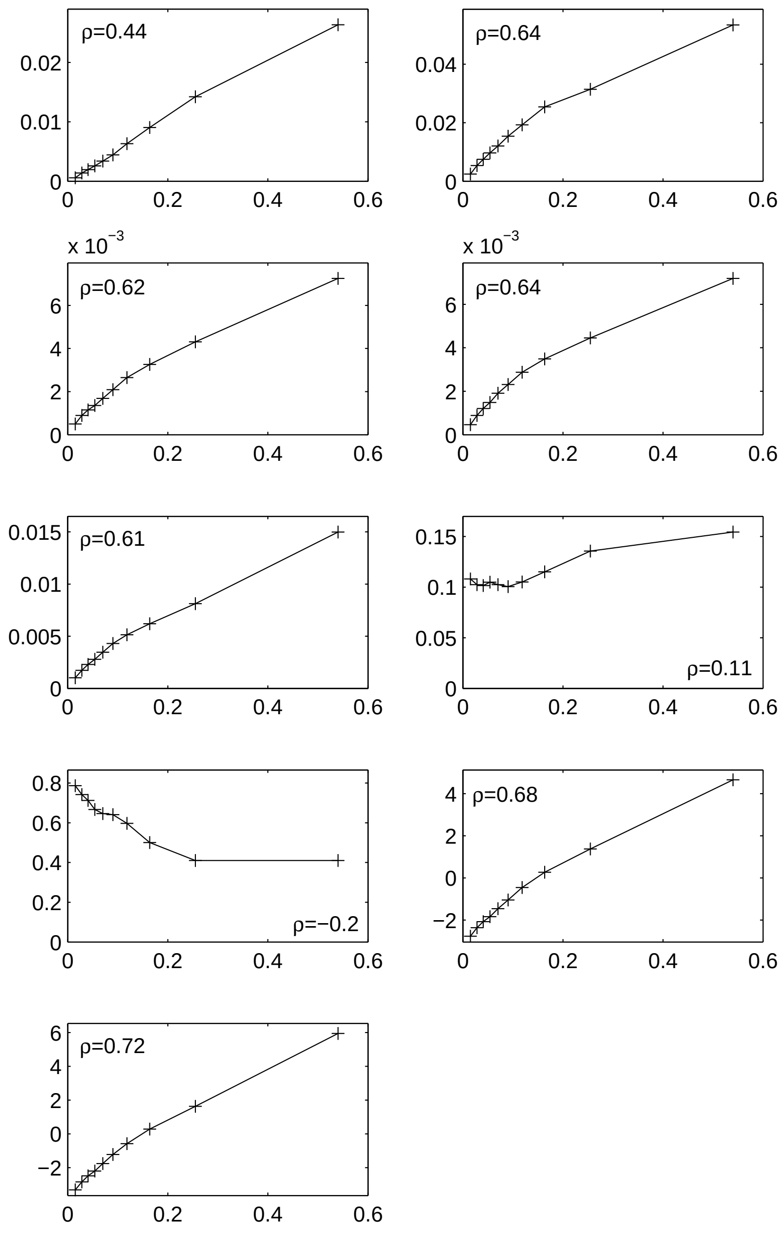

Figure 5: *The relation between liquidity proxies and bond volatility.*
This graph plots the relation between bond volatility and each of the nine liquidity measures, showing median values of both variables for each subsample formed according to the $VOLAADJ$ decile. From upper left to lower right, liquidity measures include, Amihud, σ_{Amihud}, IRC, σ_{IRC}, Roll, Turnover, ZeroTrading, λ_{DN}, λ (from upper left to lower right).

List of Tables

Table 1: *Descriptive Statistics for Credit Spreads.*
This table provides the percentiles of the distribution of credit spreads (in percent) for different ratings.

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}	*Obs*
ALL	0.096	0.602	1.264	2.754	26.774	19,615
AAA	0.041	0.264	0.495	0.893	4.910	1,426
AA	0.021	0.505	0.927	1.739	6.631	3,613
A	0.211	0.561	0.969	2.037	15.030	8,672
BBB	0.337	0.891	1.791	3.471	29.685	3,317
Speculative	0.751	2.849	4.685	7.759	61.999	2,587

Table 2: *Descriptive Statistics for Liquidity Measures.*
This table provides the percentiles of the distribution of the seven liquidity proxies employed in this study. The exact definitions are outlined in Section 3.2.2.

(a) Aggregate Sample

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$Amihud$	0.000	0.001	0.005	0.013	0.093
σ_{Amihud}	0.000	0.006	0.014	0.029	0.152
IRC	0.000	0.001	0.002	0.004	0.017
σ_{IRC}	0.000	0.001	0.002	0.004	0.019
$Roll$	0.000	0.002	0.004	0.008	0.052
$Turnover$	0.007	0.060	0.111	0.187	0.997
$ZeroTrading$	0.000	0.333	0.641	0.839	0.968
λ_{DN}	−3.165	−2.218	−1.137	0.933	13.821
λ	−3.692	−2.609	−1.367	1.056	16.717
$Observations$					19,615

(b) Bonds rated A and above

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$Amihud$	0.000	0.001	0.004	0.011	0.077
σ_{Amihud}	0.000	0.006	0.013	0.025	0.117
IRC	0.000	0.001	0.002	0.003	0.013
σ_{IRC}	0.000	0.001	0.002	0.004	0.014
$Roll$	0.000	0.002	0.003	0.006	0.034
$Turnover$	0.008	0.062	0.113	0.186	0.845
$ZeroTrading$	0.000	0.279	0.578	0.810	0.968
λ_{DN}	−3.155	−2.277	−1.362	0.380	10.592
λ	−3.692	−2.709	−1.665	0.332	12.302
$Observations$					13,711

(c) Bonds rated below A

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$Amihud$	0.000	0.002	0.006	0.018	0.118
σ_{Amihud}	0.000	0.005	0.018	0.041	0.195
IRC	0.000	0.001	0.003	0.006	0.022
σ_{IRC}	0.000	0.001	0.003	0.006	0.025
$Roll$	0.000	0.003	0.006	0.012	0.082
$Turnover$	0.006	0.055	0.107	0.191	1.545
$ZeroTrading$	0.016	0.508	0.746	0.873	0.968
λ_{DN}	−3.180	−2.011	−0.419	2.447	17.968
λ	−3.690	−2.242	−0.374	3.035	21.905
$Observations$					5,904

Table 3: *Correlation between Liquidity Measures.*
This table displays the correlations between liquidity measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) $Amihud$	1.00								
(2) σ_{Amihud}	0.58	1.00							
(3) IRC	0.72	0.70	1.00						
(4) σ_{IRC}	0.47	0.74	0.80	1.00					
(5) $Roll$	0.47	0.50	0.59	0.47	1.00				
(6) $Turnover$	-0.09	-0.04	-0.04	0.01	-0.07	1.00			
(7) $ZeroTrading$	0.09	-0.02	0.08	-0.08	0.18	-0.29	1.00		
(8) λ_{DN}	0.80	0.87	0.93	0.87	0.58	-0.05	0.02	1.00	
(9) λ	0.79	0.85	0.92	0.84	0.73	-0.06	0.06	0.98	1.00

Table 4: *Descriptive Statistics for Bond Volatility Measures.*
This table provides the percentiles of the distribution of all bond volatility measures employed in this study. The exact definitions are outlined in Section 3.2.3.

(a) Aggregate Sample

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$VOLA$	0.001	0.003	0.006	0.011	0.102
$VOLAADJ$	0.008	0.041	0.080	0.164	1.460
$RANGE$	0.003	0.016	0.030	0.058	0.493
$RANGEADJ$	0.024	0.183	0.423	1.040	12.458
$Observations$					$19,615$

(b) Bonds rated A and above

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$VOLA$	0.001	0.003	0.005	0.009	0.064
$VOLAADJ$	0.008	0.038	0.071	0.135	0.963
$RANGE$	0.003	0.015	0.026	0.048	0.386
$RANGEADJ$	0.026	0.178	0.399	0.912	10.082
$Observations$					$13,711$

(c) Bonds rated below A

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$VOLA$	0.001	0.005	0.009	0.017	0.169
$VOLAADJ$	0.007	0.052	0.111	0.249	2.096
$RANGE$	0.003	0.021	0.043	0.093	0.545
$RANGEADJ$	0.022	0.198	0.496	1.531	17.390
$Observations$					$5,904$

Table 5: *Correlation between Proxies for Bond Volatility.*
This table displays the correlations between proxies for bond volatility.

	(1)	(2)	(3)	(4)
(1) $VOLA$	1.00			
(2) $VOLAADJ$	0.58	1.00		
(3) $RANGE$	0.72	0.70	1.00	
(4) $RANGEADJ$	0.47	0.74	0.80	1.00

Table 6: *Descriptive Statistics for Credit Risk Measures.*
This table provides the percentiles of the distribution of all credit risk measures employed in this study. The exact definitions are outlined in Section 3.2.4.

(a) Aggregate Sample

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$TLMTA$	0.235	0.565	0.820	0.917	0.997
$NIMTAAVG$	−0.018	0.001	0.003	0.007	0.015
$CASHMTA$	0.005	0.027	0.061	0.123	0.289
MB	0.052	1.073	1.575	2.318	6.531
$RSIZE$	−9.205	−7.406	−6.258	−4.929	−3.864
$PRICE$	0.423	2.708	2.708	2.708	2.708
$EXRETAVG$	−0.175	−0.020	−0.004	0.011	0.055
$SIGMA$	0.107	0.182	0.270	0.405	2.188
Observations					19,615

(b) Bonds rated A and above

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$TLMTA$	0.233	0.602	0.839	0.916	0.997
$NIMTAAVG$	−0.006	0.002	0.003	0.006	0.014
$CASHMTA$	0.005	0.027	0.061	0.128	0.289
MB	0.050	1.129	1.602	2.335	4.480
$RSIZE$	−8.780	−6.541	−5.641	−4.686	−3.852
$PRICE$	1.200	2.708	2.708	2.708	2.708
$EXRETAVG$	−0.161	−0.017	−0.005	0.009	0.047
$SIGMA$	0.103	0.168	0.247	0.376	2.034
Observations					13,711

(c) Bonds rated below A

	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
$TLMTA$	0.235	0.500	0.710	0.929	0.996
$NIMTAAVG$	−0.044	−0.001	0.003	0.009	0.016
$CASHMTA$	0.005	0.026	0.060	0.119	0.249
MB	0.063	0.943	1.494	2.248	8.688
$RSIZE$	−9.366	−8.385	−7.641	−6.934	−4.712
$PRICE$	−0.174	2.423	2.708	2.708	2.708
$EXRETAVG$	−0.304	−0.026	−0.003	0.016	0.064
$SIGMA$	0.126	0.232	0.327	0.480	2.324
Observations					5,904

Table 7: *Correlation between Credit Spreads and Explanatory Variables.*
This table displays the correlations between credit spreads and our main measures of bond illiquidity (λ) and volatility ($VOLAADJ$), as well as all credit risk controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) CS	1.00										
(2) λ	0.36	1.00									
(3) $VOLAADJ$	0.53	0.72	1.00								
(4) $TLMTA$	0.51	0.47	0.59	1.00							
(5) $NIMTAAVG$	0.06	-0.09	-0.04	-0.07	1.00						
(6) $CASHMTA$	-0.02	0.09	0.08	0.18	-0.29	1.00					
(7) MB	0.51	0.58	0.70	0.50	-0.04	-0.02	1.00				
(8) $RSIZE$	0.50	0.47	0.80	0.47	0.01	-0.08	0.74	1.00			
(9) $PRICE$	0.26	0.17	0.19	0.15	0.07	-0.29	0.20	0.21	1.00		
(10) $EXRETAVG$	-0.50	-0.23	-0.33	-0.33	-0.04	0.14	-0.32	-0.31	-0.59	1.00	
(11) $SIGMA$	0.11	0.08	0.08	0.04	0.03	-0.21	0.09	0.10	0.41	-0.25	1.00

Table 8: *Estimates of Bond-Level Regressions.*
This table reports results from pooled linear regressions of end of quarter credit spreads on illiquidity, bond volatility and credit risk controls. Standard errors are adjusted for two-way clustering following Petersen (2009). The exact definitions of all measures are outlined in Section 3.2.1, Section 3.2.2, Section 3.2.3, and Section 3.2.4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	2.729^a	0.327^a	0.610^a	10.220^a	9.851^a	7.642^a	7.936^a
	(0.324)	(0.111)	(0.143)	(3.384)	(2.897)	(2.675)	(2.598)
λ	0.743^a		0.153^a		0.279^a		0.113^a
	(0.137)		(0.044)		(0.045)		(0.028)
$VOLAADJ$		15.265^a	13.466^a			7.386^a	6.115^a
		(1.257)	(1.291)			(0.842)	(0.789)
$TLMTA$				-0.037	-0.183	-0.438	-0.429
				(0.579)	(0.516)	(0.441)	(0.447)
$NIMTAAVG$				-94.943^b	-81.974^b	-86.207^b	-82.434^b
				(43.162)	(40.397)	(37.939)	(37.763)
$CASHMTA$				-0.878	-0.795	-0.742	-0.732
				(1.993)	(1.628)	(1.493)	(1.440)
MB				0.332^b	0.278^b	0.203^c	0.203^c
				(0.150)	(0.121)	(0.112)	(0.109)
$RSIZE$				-0.489^a	-0.450^a	-0.498^a	-0.481^a
				(0.123)	(0.092)	(0.088)	(0.082)
$PRICE$				-4.828^a	-4.350^a	-3.753^a	-3.743^a
				(1.153)	(1.016)	(0.933)	(0.915)
$EXRETAVG$				-13.360^a	-13.790^a	-7.365^b	-8.571^b
				(3.419)	(3.056)	(3.688)	(3.499)
$SIGMA$				4.006^a	2.797^a	1.793^a	1.682^a
				(0.670)	(0.733)	(0.574)	(0.583)
$AdjR^2$	0.340	0.537	0.544	0.645	0.677	0.699	0.703

^{a,b,c} Statistically significant at the one, five or ten percent level, respectively.

Table 9: *Estimates of Firm-Level Linear Regressions.*
This table reports results from pooled linear regressions of end of quarter credit spreads on illiquidity, bond volatility and credit risk controls. All measures are aggregated to firm level data by computing their average of all issues for each firm-quarter, reducing the number of observations to 4,508. The exact definitions of all measures are outlined in Sections 3.2.1-3.2.4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	2.904^a	0.222^a	0.267^a	9.026^a	9.006^a	5.203^a	5.380^a
	(0.057)	(0.053)	(0.065)	(0.582)	(0.548)	(0.505)	(0.509)
λ	0.800^a		0.022		0.344^a		0.042^a
	(0.016)		(0.019)		(0.014)		(0.016)
$VOLAADJ$		19.486^a	19.176^a			12.371^a	11.791^a
		(0.230)	(0.346)			(0.300)	(0.373)
$TLMTA$				0.255	0.269	0.003	0.016
				(0.243)	(0.228)	(0.207)	(0.207)
$NIMTAAVG$				-29.120^a	-13.974^c	-6.719	-5.922
				(7.737)	(7.308)	(6.612)	(6.614)
$CASHMTA$				0.544	-0.105	-0.921	-0.932
				(0.726)	(0.684)	(0.619)	(0.619)
MB				0.382^a	0.320^a	0.245^a	0.243^a
				(0.040)	(0.038)	(0.034)	(0.034)
$RSIZE$				-0.446^a	-0.412^a	-0.488^a	-0.482^a
				(0.039)	(0.036)	(0.033)	(0.033)
$PRICE$				-4.784^a	-4.372^a	-3.312^a	-3.331^a
				(0.136)	(0.129)	(0.121)	(0.121)
$EXRETAVG$				-13.140^a	-14.399^a	-7.871^a	-8.271^a
				(1.484)	(1.397)	(1.270)	(1.278)
$SIGMA$				5.600^a	3.749^a	1.529^a	1.494^a
				(0.180)	(0.186)	(0.182)	(0.183)
$Adj R^2$	0.353	0.615	0.615	0.624	0.667	0.727	0.728

[a,b,c] Statistically significant at the one, five or ten percent level, respectively.

Table 10: *Estimates of Firm-Level Linear Regressions.*
This table reports results from pooled linear regressions of end of quarter credit spreads on illiquidity, bond volatility and credit risk controls. All measures are aggregated to firm level data by computing their average of all issues for each firm-quarter, reducing the number of observations to 4,508. The exact definitions of all measures are outlined in Sections 3.2.1-3.2.4.

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	6.007^a	5.079^a	2.893^a	2.977^a	12.401^a	10.074^a
	(1.128)	(0.699)	(0.508)	(0.508)	(2.535)	(2.227)
λ		0.594^a		0.082^b		0.082^a
		(0.145)		(0.040)		(0.024)
$VOLAADJ$			13.411^a	12.497^a		5.341^a
			(1.609)	(1.726)		(0.791)
Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes
CR controls	No	No	No	No	Yes	Yes
$Adj R^2$	0.253	0.442	0.608	0.610	0.689	0.727

^{a,b,c} Statistically significant at the one, five or ten percent level, respectively.

Table 11: *Regression Estimates for Different Rating Groups.*
This table reports results from pooled linear regressions of end of quarter credit spreads on illiquidity, bond volatility and credit risk controls for subgroups of our sample formed according to the rating observed for a bond quarter. The upper two panels split the sample into bonds with a rating of A and above and those with a rating below A. The third panel reports regression estimates for a subsample of the bonds included in the second panel, namely those with a speculative grade rating. Standard errors are adjusted for two-way clustering following Petersen (2009). The exact definitions of all measures are outlined in Sections 3.2.1-3.2.4.

(a) Bonds rated A and above (N=13,711)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	1.842^a	0.529^a	0.709^a	3.622	3.545	2.861	2.972
	(0.270)	(0.124)	(0.180)	(2.854)	(2.700)	(2.529)	(2.507)
λ	0.375^a		0.092^b		0.125^a		0.066^b
	(0.095)		(0.039)		(0.027)		(0.033)
$VOLAADJ$		8.576^a	7.588^a			3.164^a	2.534^a
		(1.501)	(1.838)			(0.631)	(0.822)
CR controls	No	No	No	Yes	Yes	Yes	Yes
$AdjR^2$	0.227	0.412	0.421	0.591	0.610	0.620	0.624

(b) Bonds rated below A including speculative grade bonds (N=5,904)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	3.983^a	0.975^a	1.080^a	7.526^a	7.744^a	5.054^a	5.409^a
	(0.389)	(0.264)	(0.304)	(2.580)	(2.128)	(1.494)	(1.473)
λ	0.962^a		0.078		0.322^a		0.089^a
	(0.153)		(0.053)		(0.047)		(0.029)
$VOLAADJ$		19.040^a	18.107^a			9.054^a	7.976^a
		(1.398)	(1.517)			(1.055)	(1.259)
CR controls	No	No	No	Yes	Yes	Yes	Yes
$AdjR^2$	0.397	0.633	0.634	0.696	0.723	0.747	0.749

(c) Speculative grade bonds (N=2,587)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	4.887^a	1.609^a	1.635^a	2.518	3.603	0.121	0.665
	(0.399)	(0.335)	(0.390)	(4.801)	(4.343)	(4.532)	(4.562)
λ	1.078^a		0.026		0.381^a		0.092^b
	(0.175)		(0.083)		(0.065)		(0.046)
$VOLAADJ$		20.022^a	19.709^a			9.654^a	8.523^a
		(1.927)	(2.554)			(1.139)	(1.455)
CR controls	No	No	No	Yes	Yes	Yes	Yes
$AdjR^2$	0.409	0.637	0.637	0.692	0.722	0.746	0.747

[a,b,c] Statistically significant at the one, five or ten percent level, respectively.