Corporate bond liquidity before and after the onset of the subprime crisis

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Abstract

We analyze liquidity components of corporate bond spreads by combining the superior data quality of transaction-level corporate bond prices from TRACE with the increase in bond spreads caused by the crisis. A single linear combination of four liquidity proxies captures most of the liquidity-related variation of spreads before and during the crisis. The contribution to spreads from illiquidity increases dramatically with the crisis. We use our measure to shed new light on flight-to-quality, liquidity risk, the impact of trading frequency, the role of funding shocks to lead underwriters, and the liquidity of corporate bonds issued by financial firms.

Keywords: Corporate bonds; Liquidity; Liquidity risk; TRACE; Subprime crisis;

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1 Introduction

The onset of the subprime crisis caused a dramatic widening of corporate bond spreads. In light of the strong evidence that illiquidity in addition to credit risk contributes to corporate bond spreads, it is reasonable to believe that at least part of the spread widening can be attributed to a decrease in bond liquidity, and perhaps to an increase in liquidity *risk* as well. To show this we need robust measures of liquidity and liquidity risk which enable us to disentangle the credit risk component and the liquidity component of corporate bond spreads. Ideally, a robust measure should be significant before and after the crisis, and we would expect it to reveal a strong decrease in liquidity around the onset of the crisis.

We show in this paper that a sum of four liquidity proxies has been a consistent contributor to corporate bond spreads both before and after the onset of the crisis and across rating categories. The four variables are Amihud's measure of price impact, a measure of roundtrip cost of trading, and the variability of each of these two measures. We can think of the Amihud measure and the roundtrip cost measure as measuring liquidity, and the two variability measures as representing liquidity risk.

We arrive at our liquidity measure through a principal component analysis which reveals that the first principal component among eight liquidity variables is almost the same before and after the onset of the crisis and it is close to being an equally weighted sum of the four variables mentioned above. When we regress corporate bond spreads on the principal components, and control for credit risk, only the first component contributes to corporate bond spreads consistently across ratings and regime. In this sense our liquidity measure dominates trading frequency of bonds used in Chen, Lesmond, and Wei (2007) and Roll's bid-ask measure used by Bao, Pan, and Wang (2009). This consistency is important for drawing conclusions when we split the sample by industry and lead underwriter as explained below.

We use our liquidity measure to identify the contribution of liquidity to corporate bond spreads before and after the onset of the crisis, across different rating categories and across maturity. The procedure we use is to first compute our liquidity measure for each bond in the sample. Within a rating category, we then order the bonds according to this measure. Higher values correspond to lower liquidity. We then compute the difference between the 5% and the 50% quantiles and multiply by the regression coefficient for that rating category. The result is the liquidity-related difference between the spread of bonds with median and with high liquidity.

How large is then the effect of liquidity on spreads? Before the crisis, it was small for investment grade bonds both as a fraction of the yield spread and measured in basis points. The contribution to spreads from lack of liquidity rose through both an increase in our liquidity measure and in the sensitivity to this measure across all rating categories at the onset of the crisis, although the AAA contribution remains small during the crisis. Our finding that liquidity components in AAA-rated bonds are small even after the onset of the crisis is consistent with a flight-to-quality into those bonds. Measured as a fraction of spreads, there was almost no change in the liquidity component for speculative grade bonds. When we zoom in on the time series behavior of liquidity premia, we find that they persistently increase for investment grade bonds during the crisis and peak around the rapid stock market decline in the first quarter of 2009. For speculative grade bonds, premia are less persistent, peak around the Lehman default in the fall of 2008, and returned almost to pre-crisis levels in the summer of 2009.

Our measure is also useful for analyzing other aspects of corporate bond illiquidity. We construct a liquidity beta, i.e. a measure for the covariation of an individual bond's liquidity with that of the entire corporate bond market. We show that this liquidity beta is not a significant contributor to spreads before the onset of the crisis but it does contribute to spreads for bonds except for AAA-rated bonds after the onset of the crisis. This indicates that the flight-to-quality effect in investment grade bonds found in Acharya, Amihud, and Bharath (2010) is confined to AAA-rated bonds. We also ask whether financial distress of a lead underwriter of a corporate bond issue affects the liquidity of the bond in the secondary market. If lead underwriters are providers of liquidity of the bond in secondary market trading, it is conceivable that if a lead underwriter is in financial distress, the liquidity of the bond decreases relative to other bonds. We show that bonds which had Bear Stearns as lead underwriter had lower liquidity during the take-over of Bear Stearns and bonds with Lehman as lead underwriter had lower liquidity around the bankruptcy of Lehman. Finally, we investigate whether the time series variation of liquidity of corporate bonds issued by financial firms is different from the variation for bonds issued by industrial firms. There is conflicting empirical evidence on this issue: Longstaff, Mithal, and Neis (2005) find that bonds issued by financial firms are more illiquid than other bonds, while Friewald, Jankowitsch, and Subrahmanyam (2009) find this not to be the case. Our time series study reveals that bonds issued by financial firms have similar liquidity as bonds issued by industrial firms, except in extreme stress periods, where bonds of financial firms become very illiquid, overall and compared to bonds issued by industrial firms.

The detailed trading data for corporate bonds available from the TRACE database are critical for our ability to measure liquidity proxies properly, and they help us shed new light on previous results on liquidity in corporate bonds. We show that Datastream's record of zero return days for a bond, which in Chen, Lesmond, and Wei (2007) is used to proxy for days when the bond does not trade, has little connection to the actual trades recorded in TRACE. With actual trades, the LOT measure employed in Chen, Lesmond, and Wei (2007) becomes unrealistically large. We also show that the Amihud measure is strongly influenced by restricting the universe of trades to large trades, as we do in this paper. Using large trades only, the median price impact of a 300.000 dollar trade is roughly 0.1%, whereas Han and Zhou (2008) using all trades obtain an impact of 10.2%.

To support the claim that our measure is not measuring credit risk, we run regressions on a matched sample of corporate bonds using pairs of bonds issued by the same firm with maturity close to each other. Instead of credit controls, we use a dummy variable for each matched pair and estimate the response of spreads to our liquidity measure. The measure remains significant. In an appendix, we also show that our regression results change only slightly if we choose Treasury instead of swap rates as our riskless rates, and we test for simultaneous equation bias arising from joint determination of credit and liquidity risk and for omitted variables.

The flow of our paper is as follows. We describe our data set and how we define the eight liquidity variables that enter into the regressions. After providing summary statistics of our liquidity proxies, we run regressions on the eight liquidity variables one at a time while controlling for credit risk. We see that four variables stand out as significant predictors of spreads. Remarkably, these four variables also form the first component in a principal component decomposition of the standardized liquidity variables - and this decomposition is stable before and after the onset of the crisis. We then perform the same regressions as above - using one principal component at a time instead of the liquidity proxies. The first principal component is the only consistently significant regressor variable. Since the principal component is close to being an equally weighted sum of the four liquidity variables, we define an operational measure of liquidity as the sum of the four variables. This measure is then used to measure the contribution of illiquidity to corporate bond spreads across ratings and maturities, before and after the onset of the crisis. Furthermore, we use our measure to examine how the covariance between bond-specific liquidity and market-wide liquidity affects bond spreads, and how financial distress of a lead underwriter and the type of firm issuing the bond affect bond liquidity.

2 Literature review

It has been recognized for a long time that the ease with which a security is traded influences its price. A comprehensive survey of both the different notions of and the empirical evidence on liquidity can be found in Amihud, Mendelson, and Pedersen (2005). Here, we will focus on the growing literature that deals specifically with corporate bonds.

In recent years, the illiquidity of corporate bonds has been seen as a possible explanation for the 'credit risk puzzle', i.e. the claim that yield spreads on corporate bonds are larger than what can be explained by default risk - even after adjusting for recovery risk and compensation for bearing default risk. Huang and Huang (2003) calibrate structural default risk models to match the default probabilities and recoveries of corporate bonds. They use a specification of the risk premium - learned from equity markets - to price the default risk in corporate bonds and show that the resulting credit spreads are smaller than the observed spreads. Other works supporting the idea that there are components of credit spreads that are unrelated to default risk include Elton, Gruber, Agrawal, and Mann (2001) who show that yield spreads cannot entirely be explained by credit risk and tax effects, and Collin-Dufresne, Goldstein, and Martin (2001) who show that changes in credit spreads cannot be explained by credit risk alone. Covitz and Downing (2007) study credit spread components in the short maturity commercial paper market and while they do find evidence of a contribution to spreads from illiquidity, they find credit risk to be the main determinant of spreads for short maturities. Longstaff, Mithal, and Neis (2005) subtract CDS premia from bond spreads to extract a non-default component of a corporate bond spread. They show that this component is correlated with proxies for liquidity both in the cross section of corporate bond spreads and in the time series evolution of spreads. In our paper, we cover a larger segment of the corporate bond market than those for which CDS premia exist. Also, it is frequently the case that the CDS spread is larger than the comparable bond spread indicating that the CDS market may also be prone to buying and selling pressures. This suggests that there are also liquidity components in CDS spreads as confirmed by Bongaerts, Driessen, and de Jong (2009).

Earlier papers which show that liquidity proxies are significant explanatory variables for corporate bond spreads and bond returns are Houweling, Mentink, and Vorst (2005)), Downing, Underwood, and Xing (2005), and de Jong and Driessen (2006). An early contribution, which also stresses the importance of matrix pricing for empirical studies of bond liquidity, is Sarig and Warga (1989).

TRACE transactions data became available only recently, and therefore few studies have used the data set. Bao, Pan, and Wang (2009) use TRACE data to study liquidity effects focusing in particular on a transformation of the Roll measure. There are several studies on the effects of the introduction of TRACE. These show that the enhanced price transparency following the dissemination of prices has lowered transaction costs for investors, see Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), and Bessembinder, Maxwell, and Venkaraman (2006). This would suggest that liquidity has increased. However, as shown in Goldstein, Hotchkiss, and Sirri (2007) trading volume and trading frequency have not increased as a consequence of bond price dissemination, and it is still the case that a large number of bonds trade very infrequently. This is also confirmed by Mahanti, Nashikkar, Subramanyam, Chacko, and Mallik (2008). They combine data on holdings on corporate bonds by different investors with turnover measures of these investor's portfolios to infer a turnover measure for bonds, called latent liquidity. This measure is shown to have predictive power for other measures of liquidity. However, since we are interested in yield spread effects of illiquidity, we must confine ourselves to the more liquid segment of the corporate bond market for which we can actually observe some trading and therefore some prices and price changes. Friewald, Jankowitsch, and Subrahmanyam (2009) and Han and Zhou (2008) are other papers using the TRACE data set.

3 Data description

Since January 2001 members of the Financial Industry Regulatory Authority (FINRA) have been required to report their secondary over-the-counter corporate bond transactions through TRACE (Trade Reporting and Compliance Engine). Because of the uncertain benefit to investors of price transparency not all trades reported to TRACE were initially disseminated at the launch of TRACE July 1, 2002. Beginning October 1, 2004 trades in almost all bonds except some lightly traded bonds are disseminated (see Goldstein and Hotchkiss (2008) for details). Therefore our sample starts on this date.

We use a sample of straight coupon bullet bonds with trade reports from October 1, 2004 to June 30, 2009. That is, we require that bonds are fixed rate bullet bonds that are not callable, convertible, putable, or have sinking fund provisions. We obtain bond information from Bloomberg, and this provides us initially with 10.785 bond issues. We use rating from Datastream and bonds with missing rating are excluded.[1] This reduces the sample to 5.376 bonds. For these bonds we collect the trading history from TRACE covering the period from October 1, 2004 to June 30, 2009 and after filtering

[1]We use the rating from S&P. If this rating is missing we use the rating from Moody's and if this is missing the rating from Fitch. If we still do not have a rating we use the company rating.

out erroneous trades, as described in Dick-Nielsen (2009), we are left with 8.212.990 trades. Finally we collect analysts' forecast dispersion from IBES, share prices for the issuing firms and firm accounting figures from Bloomberg, swap rates from Datastream, Treasury yields consisting of the most recently auctioned issues adjusted to constant maturities published by the Federal Reserve in the H-15 release[2] and LIBOR rates from British Bankers' Association. If forecast dispersion, share prices, or firm accounting figures are not available, we drop the corresponding observations from the sample.

4 Empirical methodology

This section provides details on the regression analysis conducted in the next section and defines the set of liquidity variables we use.

4.1 Regression

As dependent variable we use the yield spread for every bond at the end of each quarter in the regressions. We calculate the quarter-end yield as the average yield for all trades on the last day in the quarter where the bond traded. If a bond did not trade during the last month of the quarter, it is excluded from that quarter. Retail-sized trades (trade below $100,000 in volume) are discarded. Yield spreads are calculated as the difference between the quarter-end yield and the interpolated maturity-matched swap rate calculated on the same day as the yield is measured. We exclude yield spreads for bonds that have less than one month to maturity or have a time

[2]Further information about the Treasury yield curve methodology can be found on the United States Department of Treasury's web page http://www.treas.gov/offices/domestic-finance/debt-management/interest-rate/yieldmethod.html.

to maturity when issued of more than 30 years.

To control for credit risk, we follow Blume, Lim, and MacKinlay (1998) and others and add the ratio of operating income to sales, ratio of long term debt to assets, leverage ratio, equity volatility and four pretax interest coverage dummies to the regressions.[3] In order to capture effects of the general economic environment on the credit risk of firms we include the level and slope of the swap curve, defined as the 10-year swap rate and the difference between the 10-year and 1-year swap rate. Duffie and Lando (2001) show that credit spreads may increase when there is incomplete information on the firm's true credit quality. To proxy for this effect, we follow Güntay and Hackbarth (2006) and use dispersion in earnings forecasts as a measure of incomplete information.

Finally we add bond age, time-to-maturity, and size of coupon to the regressions - see for example Sarig and Warga (1989), Houweling, Mentink, and Vorst (2005) and Longstaff, Mithal, and Neis (2005).

For each rating class we run separate regressions using quarterly obser-

[3]The pretax interest coverage dummies are defined as follows. We define the pretax interest rate coverage (IRC) ratio as EBIT divided by interest expenses. It expresses how easily the company can cover it's interest rate expenses. However, the distribution is highly skewed. As in Blume, Lim, and MacKinlay (1998) we control for this skewness by creating four dummies (pretax dummies) which allows for a non-linear relationship with the spread. The first dummy is set to the IRC ratio if it is less than 5 and 5 if it is above. The second dummy is set to 0 if IRC is below 5, to the IRC ratio minus 5 if it lies between 5 and 10 and 5 if it lies above. The third dummy is set to 0 if IRC is below 10, to the IRC ratio minus 10 if it lies between 10 and 20 and 10 if it lies above. The fourth dummy is set to 0 if IRC is below 20 and is set to IRC minus 20 if it lies above 20 (truncating the dummy value at 80).

vations. The regressions are

$$\begin{aligned}
\text{Spread}_{it} = \alpha &+ \gamma \text{ Liquidity}_{it} + \beta_1 \text{ Bond Age}_{it} + \beta_2 \text{Amount Issued}_{it} \\
&+ \beta_3 \text{ Coupon}_{it} + \beta_4 \text{Time-to-Maturity}_{it} + \beta_5 \text{ Eq.Vol}_{it} \\
&+ \beta_6 \text{ Operating}_{it} + \beta_7 \text{ Leverage}_{it} + \beta_8 \text{ Long Debt}_{it} \\
&+ \beta_{9,pretax} \text{ Pretax dummies}_{it} + \beta_{10} \text{ 10y Swap}_t \\
&+ \beta_{11} \text{ 10y-2y Swap}_t + \beta_{12} \text{ forecast dispersion}_{it} + \epsilon_{it} \qquad (1)
\end{aligned}$$

where i is bond issue, t is quarter, and Liquidity$_{it}$ contains one of the liquidity proxies defined below. Since we have panel data set of yield spreads with each issuer potentially having more than one bond outstanding at any point in time we calculate two-dimensional cluster robust standard errors (see Petersen (2009)). This corrects for time series effects, firm fixed effects and heteroscedasticity in the residuals.

4.2 Liquidity Measures

Since there is no single measure that adequately describes the liquidity of an asset, we define several liquidity-related measures for corporate bonds in this section. We winsorize the 0.5% highest values of every liquidity variable, meaning that all values above the 99.5% percentile are set to the 99.5% percentile.

4.2.1 Amihud measure (price impact of trades)

Amihud (2002) constructs an illiquidity measure that is based on the theoretical model of Kyle (1985). It measures the price impact of a trade per unit traded and we use a slightly modified version of this measure. For each corporate bond the measure is the daily average of absolute returns r_j divided by trading volume Q_j (in million \$) of consecutive transactions:

$$Amihud_t = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|r_j|}{Q_j} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|\frac{P_j - P_{j-1}}{P_{j-1}}|}{Q_j}$$

where N_t is the number of returns on day t. At least two transactions are required on a given day in order to calculate the measure, and we define a quarterly Amihud measure by taking the median of daily measures within the quarter.

4.2.2 Roll measure (bid-ask spread)

A liquid asset can be bought or sold close to the fundamental price of the asset, implying that roundtrip costs are small. A proxy for roundtrip costs is the bid-ask spread, but bid-ask spreads are not available in TRACE. Since November 2008, buy-sell indicators are available, but this covers only a fraction of our sample. Roll (1984) finds that under certain assumptions the effective bid-ask spread equals two times the square root of minus the covariance between adjacent price changes:

$$Roll_t = 2\sqrt{-cov(\Delta P_i, \Delta P_{i-1})}$$

where t is the time period for which the measure is calculated. The intuition is that the bond price bounces back and forth within the bid-ask band, and higher bid-ask bands lead to higher negative covariance between adjacent price changes. We define a daily Roll measure using a rolling window of 21 trading days, and the measure is only well-defined if there are at least four transactions in the window. We define a quarterly Roll measure by taking the median of daily measures within the quarter.

4.2.3 Unique roundtrip cost (bid-ask spread)

An alternative measure of transaction costs, proposed in Feldhütter (2010), is calculated using *unique roundtrip trades* (URT). Often, we see a corporate bond trading two or three times within a very short period of time after a longer period with no trades. This is likely to occur because a dealer matches a buyer and a seller and collects the bid-ask spread as a fee. When a dealer has found a match, a trade between seller and dealer along with a trade between buyer and dealer are carried out. Possibly, the matching occurs through a second dealer in which case there is also a transaction between the two dealers. If two or three trades in a given bond with the same volume take place on the same day, and there are no other trades with the same volume on that day, we define the transactions as part of a URT. For a URT we define the unique roundtrip cost (URC) as

$$\frac{P_{max} - P_{min}}{P_{max}}$$

where P_{max} is the largest price in the URT and P_{min} is the smallest price in the URT. A daily estimate of roundtrip costs is the average of roundtrip costs on this day for different volumes, and we estimate quarterly roundtrip costs by averaging over daily estimates. URC overcomes the problem that we only have information on trading volume and not, as in Green, Hollifield, and Schürhoff (2007), on bid and ask prices or dealer identity. Feldhütter (2010) examines the properties of URTs in detail, including how much of total trading volume is captured and for a subsample of TRACE data with buy-sell indicators available, to what extent URTs capture full roundtrip costs.

4.2.4 Turnover (trading intensity)

Assets that trade frequently are intuitively more liquid than assets that only trade on rare occasions. We therefore consider the quarterly turnover of the bond:

$$\text{Turnover}_t = \frac{\text{Total trading volume}_t}{\text{Amount outstanding}}$$

where t is the quarter. We can interpret the inverse of the turnover as the average holding time of the bond, i.e. a turnover of 1 implies an average holding time of about 3 months.

4.2.5 Zero trading days (trading intensity)

An alternative trading intensity measure is the number of days where a bond did not trade. We calculate *bond zero-trading days* as the percentage of days during a quarter where the bond did not trade. We also calculate *firm zero-trading days* as the percentage of days during a quarter where none of the issuing firm's bonds traded. Clearly, this is a firm-specific rather than a bond-specific measure, and it is therefore the same for different bonds issued by the same firm. Even though a single bond seldomly trades, the issuing firm often has bonds of many different maturities outstanding. It may therefore be the case that the waiting time between trades in any of the firm's bond issues is much shorter and that there is relatively frequent new information about the issuing firm and frequent trading in close substitutes. Firm zero trading days addresses this issue.

4.2.6 Variability of Amihud and unique roundtrip costs (liquidity risk)

It is likely that investors consider not only the current level of bond liquidity but also the possible future levels in case the investor needs to sell the bond. The variability of both the Amihud measure and unique roundtrip costs may therefore play a role for liquidity spreads. Thus, we include in our regressions the standard deviations of the daily Amihud measure and unique roundtrip costs measured over one quarter. These two measures do not separate total liquidity risk into a systematic and unsystematic component. Arguably, only the systematic component is important for pricing, but since it is difficult to measure this component on a quarterly basis, we calculate the total component and address the systematic component later in the paper.

5 Liquidity premia

5.1 Summary statistics

Table 1 shows summary statistics for the liquidity variables. We see that the median quarterly turnover is 4.5%, meaning that for the average bond in the sample it takes 5-6 years to turn over once. The turnover is a lower bound on the actual turnover since trade sizes above $1mio ($5mio) for speculative (investment) grade bonds are registered as trades of size $1mio ($5mio). The median number of bond zero-trading days is 60.7% consistent with the notion that the corporate bond market is an illiquid market. We also see that the median number of firm zero-trading days is 0%. This shows that although a given corporate bond might not trade very often, the issuing firm has *some* bond that is trading. It is likely that the number of bond zero-trading days overstates the difficulty of finding a trading partner when buying or selling the bond, since the bond is a close substitute to a number of other bonds.

The median Amihud measure is 0.0044 implying that a trade of $\$300,000$ in an average bond moves price by roughly 0.13%. Han and Zhou (2008) also calculate the Amihud measure for corporate bond data using TRACE data and find a much stronger price effect of a trade. For example, they find that a trade in an average bond of $\$300,000$ moves the price by 10.2%. The reason for this discrepancy is largely due to the exclusion of small trades in our sample and underscores the importance of filtering out retail trades when estimating transaction costs of institutional investors[4].

The median roundtrip cost in percentage of the price is 0.22% according to the URC measure, while the roundtrip cost is less than 0.05% for the 5% most liquid bonds. Thus, transaction costs are modest for a large part of the corporate bond market consistent with findings in Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), and Bessembinder, Maxwell, and Venkaraman (2006). The roundtrip cost measured using URC is lower than the median roundtrip cost of 0.53% when estimated using the Roll measure.

The correlations of the liquidity measures in Panel B of Table 1 reveal several interesting aspects of liquidity and liquidity risk. The correlation of 87% between URC and URC risk and 61% between Amihud and Amihud risk shows that liquidity and liquidity risk are highly correlated. This is consistent with results in Acharya and Pedersen (2005) who likewise find a

[4]A second reason for the discrepancy is that we estimate a quarterly Amihud measure by taking the median of daily measures, while Han and Zhou (2008) estimate a monthly measure by taking the mean of daily measures. The effect of filtering out small trades is by far the most important reason for the discrepancy.

high correlation between liquidity and liquidity risk. Interestingly, there is a high correlation of 72% between market depth (Amihud) and bid/ask spread (URC).

The correlations also show that the Amihud measure is negatively correlated with firm zero, bond zero, and turnover, while the Roll measure has positive correlations with the three trading activity variables. We would expect negative correlations for both the Roll and Amihud measure, since more traded bonds are likely to have lower bid/ask spreads and higher market depth. The positive correlations for the Roll measure might be explained by the statistical properties of the Roll measure. Harris (1990) finds that the serial covariance estimator can be severally biased in small samples. The bias decreases in the number of observations, and this might explain the positive correlations between the Roll measure and trading activity measures. The bias might also explain why the Amihud measure is slightly more successful in explaining spreads than the Roll measure in the next section.

Having defined the individual liquidity measures and looked at some descriptive statistics, we now turn to the effects on bond spreads of these variables one at at time.

5.2 The effect of liquidity proxies

We have defined eight liquidity proxies and in this section we ask if the proxies affect spreads. For each variable we run the pooled regression in Equation (1) for each of the seven rating categories and before and after the onset of the subprime crisis. We windsorize the 0.5% highest and lowest spreads to make the results robust to outliers. Running separate regressions for different rating categories shows us to what extent the variables affect bonds of various credit quality and how robust our results are. In addition, the effect of liquidity on corporate bond spreads might be different in periods of rich liquidity and periods of little liquidity. By splitting the sample into pre- and post-subprime, we see how liquidity is priced in two such different regimes; the pre-subprime period was a period with plenty of liquidity while the market in the post-subprime period has suffered from a lack of liquidity. Table 2 shows the regression coefficients for each of the variables.[5]

For the pre-subprime period both measures of transaction costs, Roll and URC, have positive coefficients for every rating category. All five coefficients are significant for URC while the results are mixed in case of the Roll measure. We obtain similar results in the post-subprime period, four out of five coefficients positive and statistically highly significant in case of the URC measure and mostly insignificant results for the Roll measure. Transaction costs are clearly priced, at least when we proxy bid-ask spreads with the URC measure, which is consistent with the results in Chen, Lesmond, and Wei (2007) who find that bid/ask spreads are priced. We also see that the Amihud measure has positive regression coefficients across all ratings pre- and post-subprime and 6 out of 10 are statistically significant.

Figure 1 shows that bid-ask spreads (URC) and the lack of market depth (Amihud) have increased strongly during the subprime crisis. The increase from the beginning of the crisis to the end of 2008 in bid-ask spreads is

[5]We only use observations for which an estimate for all measures exists. This ensures that the regression coefficients for all proxies are based on the same sample. We have also run the regressions where we allow an observation to enter a regression if the observation has an estimate for this liquidity proxy, although it might not have estimates of some of the other proxies. The results are very similar.

approximately a factor of 4 for bid-ask spreads and a factor of 8 for lack of market depth. That is, not only have bid-ask spreads widened strongly during the crisis but the ability to sell large notional amounts of bonds without a sizeable discount has disappeared. We see that liquidity in the second quarter of 2009 slowly returns to the market since Amihud and URC are finally decreasing after the increase in previous years.

Volume has traditionally been regarded as a proxy for liquidity, since it should be easier to trade when markets are more active. However, Johnson (2008) finds in a simple frictionless model that volume is unrelated to the level of liquidity but related to liquidity risk as measured by the variance of liquidity. Table 2 shows that 9 out of 10 regression coefficients for volume are negative indicating that large volumes tend to reduce credit spreads. The significance of the coefficients is modest though, so the evidence is not conclusive. Liquidity risk is clearly priced since Amihud and URC risk have significantly positive regression coefficents in 19 out of 20 cases. Interestingly, all coefficients increase strongly in size post-subprime. Thus, investors require a larger compensation post-subprime for investing in bonds with a high uncertainty about the liquidity discount when selling the bond. Since liquidity risk has increased strongly as Figure 1 shows, the impact of liquidity risk is twofold; through a larger level of liquidity risk *and* through a higher risk premium on liquidity risk.

Turning to zero trading days Table 2 shows surprisingly that there is no consistent relationship between the number of zero trading days and spreads. If anything, the relationship tends to be negative since 14 out of 20 bond and firm zero regression coefficients are negative. Constantinides (1986) finds theoretically that in the presence of transaction costs, investors will trade infrequently, and consistent with this line of reasoning Chen, Lesmond, and Wei (2007) find that corporate bond spreads - when controlling for credit risk - depend positively on the number of zero trading days.

The difference between our results and those of Chen, Lesmond, and Wei (2007) is likely to be the data source. While we use actual transaction data and can directly detect when a trade occurs, Chen, Lesmond, and Wei (2007) use data fra Datastream and define a zero trading day as a day where the price does not change. We find that Datastream corporate bond data can differ substantially from actual transaction data in non-predictable ways. To illustrate this, we calculate for each bond quarter the percentage zero trading days using Datastream, and Figure 2 plots all pairs of TRACE and Datastream percentage zero trading days. The figure shows that there is very little relation between actual and Datastream zero trading days, and while Datastream often understates the number of zero trading days, they are also overstated for some observations. Although zero-trading days are not correctly identified in Datastream, the LOT measure of Chen, Lesmond, and Wei (2007) could be a relevant measure to include in our analysis. Therefore we have calculated a yearly LOT measure as in Chen, Lesmond, and Wei (2007) for all TRACE bonds for the years 2005, 2006, and 2007 based on all TRACE trades. The median roundtrip cost is 237 basis points, which appears too high compared to findings in Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), and Bessembinder, Maxwell, and Venkaraman (2006).

From a theoretical point of view the mixed results regarding the impact of zero trading days on spreads can be explained by results in Huberman and Stanzl (2005). They show that an investor trades more often when price impact of trades is high, because he attempts to reduce the total price impact by submitting more but smaller orders. All else equal more trades therefore occur in illiquid bonds since it is necessary to split a sell order in many small trades, while it can be executed in a single trade in a liquid bond.[6] If this explanation holds true we should expect to see less zero trading days in illiquid times without an increase in the total trading volume. As Figure 1 shows this happens during the subprime crisis. The top-right graph shows that the median number of percentage zeros in the regression sample decreases during the subprime crisis. For example, the median number of percentage zeros is 30% in the last quarter of 2008 while it is 62% in the first quarter of 2007. Also, we see in the bottom-left graph that volume in our regression sample decreases slightly during the crisis.

Drawing conclusions from Figure 1 might be misleading since a bond in a given quarter is only included in the regression sample if it has a full set of accounting variables and trades at least four times that quarter (otherwise the Roll measure cannot be calculated). Thus, it is only the most liquid bonds that are included and there are less bonds included post-subprime

[6]Goldstein, Hotchkiss, and Sirri (2007) find that dealers behave differently when trading liquid and illiquid bonds. When trading liquid bonds they are more likely to buy the bond, have it as inventory and sell it in smaller amounts. When trading illiquid bonds they more often quickly sell the entire position, so they perform more of a matching function in these bonds. This is consistent with our argument that illiquid bonds trade more often, which can be illustrated with the following example. In a liquid bond the investor sells $1,000,000 to a dealer, who sells it to investors in two amounts of $500,000. In an illiquid bond the investor sells 500,000 to two different dealers, who each sells the $500,000 to an investor. The total number of trades in the illiquid bond is four while it is three in the liquid bond.

than pre-subprime. The decrease in zero trading days might therefore be due to a smaller number of bonds included in the sample. To address this concern, Figure 3 shows time series of the quarterly average number of trades and average trade size for all straight coupon bullet bond transactions in our sample period. The top graphs are based on transactions of size $\$100,000$ or more, which our regression results are based on, while the bottom graphs are based on all transactions. In both cases we clearly see an increase on the average number of trades and a decrease in the average trade size after the onset of the subprime crises.

Overall, there is theoretical evidence both in favor of and against the use of zero trading days as a measure of illiquidity. Our empirical evidence is also mixed. We show that trading activity increases when the market becomes more illiquid, while at the same time Table 2 shows that bond zero trading days do tend to predict investment grade spreads after the onset of the subprime crisis. In any case, we do not find that zero trading days can be consistently used as a predictor of spreads.

5.3 Principal component analysis of liquidity

In our analysis we include eight liquidity proxies that measure different aspects of liquidity. To see if most of the relevant information in the proxies can be captured by a few factors, we conduct a principal component analysis. Table 3 shows the loadings and the explanatory power of the eight principal components. We see that both the explanatory power and the loadings of each PC component are very stable in the two subperiods. Also we see that the PC components have clear interpretations. The first component explains 40% of the variation in the liquidity variables and is close to being an equally-weighted linear combination of the Amihud and URC measures and their associated liquidity risk measures. The second PC explains 20% and is a zero trading days measure, the third PC explains 13% and is a volume measure, and the fourth PC explains 9% and is a Roll measure. The last four PCs explain less than 20% and do not have clear interpretations.

Table 4 shows results of adding each of the PCs in turn to our regression in the same way as we did with each liquidity variable in Table 2. Strikingly, the first PC is significant for all rating categories pre- and post-subprime. For 9 out of 10 regression coefficients the significance is at a 1% level. In addition, the remaining seven PCs are mostly insignificant and often with conflicting signs. This suggests that although liquidity has many different aspects, a single linear combination of measures of transaction costs, market depth, and liquidity risk explains much of the impact of liquidity on yield spreads. The factor is priced at all ratings pre- and post-subprime in contrast to previously proposed liquidity proxies, zero-trading days (Chen, Lesmond, and Wei (2007)) and the Roll measure (Bao, Pan, and Wang (2009)).

The principal component loadings on the first PC in Table 3 lead us to define a factor that loads evenly on Amihud, URC, Amihud risk, and URC risk, and does not load on any of the other liquidity measures. The factor is simpler to calculate than the first PC while retaining its properties. We use this factor in our subsequent analysis and call it λ. To be precise: for each bond i and quarter t we calculate the measure L_{it}^j where $j = 1, .., 4$ is an index for Amihud, URC, Amihud risk, and URC risk. We normalize each measure $\tilde{L}_{it}^j = \frac{L_{it}^j - \mu^j}{\sigma^j}$ where μ^j and σ^j are the mean and standard deviation of L^j across bonds and quarters and define our liquidity measure for each bond and quarter as

$$\lambda_{it} = \sum_{j=1}^{4} \tilde{L}_{it}^{j}$$

5.4 Size of liquidity component

To calculate the impact of corporate bond illiquidity on yield spreads we do the following. For each rating R we run the pooled regression

$$spread_{it}^{R} = \alpha^{R} + \beta^{R}\lambda_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i refers to bond, t to time (measured in quarters of year), and λ_{it} is our liquidity measure. We define the liquidity score for a bond in a given quarter as $\beta^{R}\lambda_{it}$. Within each rating (AAA, AA, A, BBB, spec), period (pre- or post subprime), and maturity (0-2y, 2-5y, 5-30y) we sort all observations according to their liquidity score. The liquidity component of an average bond is defined as the 50% quantile minus the 5% quantile of the liquidity score distribution. Thus, the liquidity component measures the difference in bond yields between a bond with average liquidity and a very liquid bond. Following Cameron, Gelbach, and Miller (2008) we calculate confidence bands by performing a wild cluster bootstrap of the regression residuals.

Table 5 shows the size of the liquidity component. We see that the liquidity component becomes larger as the rating quality of the bond decreases. For investment grade ratings, the component is small with an average pre-subprime across maturity of 0.8bp for AAA, 1.0bp for AA, 2.4bp for A, and 3.9bp for BBB. For speculative grade the liquidity component is larger and estimated to be 57.6bp.

There is a strong increase in the liquidity component in the post-subprime period as Panel B in Table 5 shows. The component increases by a factor 10 or more in investment grade bonds of rating AA, A, and BBB while it increases by a factor 3-4 in speculative grade bonds. This shows that liquidity has dried out under the subprime crisis and part of the spread widening for bonds is due to a higher liquidity premium. Figure 1 shows the evolution of liquidity variables over the sample, and we see that the liquidity variables entering our measure of liquidity (Amihud, URC, Amihud risk, URC risk) all increase strongly after the onset of the subprime crisis. Thus, the higher liquidity premium is due to an increase in the sensitivity of spreads to illiquidity as well as higher levels of illiquidity.

While liquidity components in all ratings increase, we see that in absolute terms the increase in AAA bonds is modest. Even after the onset of the subprime crisis the component is 8 basis points or less, which is small compared to the component of other bonds. We see in Table 5 that the regression coefficient for AAA on the first principal component is small post-subprime compared to those of other rating classes, so the sensitivity of AAA-rated bonds to liquidity is small.[7] This suggests that there is a flight-to-quality into AAA bonds, namely that investors are buying high-quality AAA-rated bonds regardless of their liquidity.

The average liquidity premium in speculative grade bonds was 57.6bp pre-subprime, so even in this liquidity-rich period speculative grade bonds commanded a sizeable liquidity premium. Post-subprime the liquidity premium increased to 196.8bp for speculative grade bonds. An A rated bond

[7]Strictly speaking, we use our measure λ to calculate liquidity components, but the regression coefficient on λ is close to the coefficient on 1PC.

has an average liquidity premium of 50.7bp post-subprime, so the illiquidity of such a bond post-subprime is similar to that of a speculative grade bond pre-subprime.

The size of the liquidity component pre-subprime is comparable in magnitude to the nondefault component in investment grade corporate bond spreads found by subtracting the CDS premium from the corporate - swap spread (swap basis), see Longstaff, Mithal, and Neis (2005), Blanco, Brennan, and Marsh (2005), and Han and Zhou (2008).[8] These papers look at recent periods before the subprime crisis and our pre-subprime results agree with their results in that there is a modest liquidity premium in investment grade corporate bond yields. The nondefault component for speculative bonds extracted from the swap basis is smaller and often negative, and the evidence presented here suggests that other factors than corporate bond liquidity are important for explaining the basis for speculative grade bonds.[9]

Turning to the term structure of liquidity, the general pattern across ratings and regime is that the liquidity component increases as maturity becomes higher. Overall, the premium in basis points is around twice as high for long maturity bonds compared to short maturity bonds. This seemingly contrasts the work of Ericsson and Renault (2006) who find a downward sloping term structure of liquidity. However, they use two data sets: one is transaction data from NAIC and the other is Datastream data, and only

[8]Longstaff, Mithal, and Neis (2005) find an average nondefault component of -7.2bp for AAA/AA, 10.5bp for A, and 9.7bp for BBB, Han and Zhou (2008) find the nondefault component to be 0.3bp for AAA, 3.3bp for AA, 6.7bp for A, and 23.5bp for BBB, while Blanco, Brennan, and Marsh (2005) find it to be 6.9bp for AAA/AA, 0.5bp for A, and 14.9bp for BBB.

[9]Longstaff, Mithal, and Neis (2005) report an average of 17.6bp for BB, while Han and Zhou (2008) estimate it to be 2.8bp for BB, -53.5bp for B, and -75.4bp for CCC.

find support for a downward sloping liquidity effect in the Datastream data set. In light of the quality of Datastream data discussed earlier in this paper, we find it likely that conclusions based on actual transaction data are more reliable than those based on Datastream data.

To address how much of the corporate bond spread is due to liquidity, we find the fraction of the liquidity component to the total spread. For each bond we proceed as follows. We define the bond's liquidity component as $\beta^R(\lambda_{it}-\lambda_{5t})$ where λ_{5t} is the 5% quantile of the liquidity scores. The liquidity component is then divided by the bond's yield spread to give an estimate of the fraction of the total yield spread that is due to illiquidity. Within each group we find the median liquidity fraction. We show later that the size of the liquidity component is robust to the choice of benchmark riskfree rate, but the liquidity fraction of the total spread is sensitive to the benchmark. The swap rate is chosen because there is mounting evidence that swap rates historically have been a better proxy for riskfree rates than Treasury yields (see for example Hull, Predescu, and White (2004) and Feldhütter and Lando (2008)).

Table 6 shows the fraction of the liquidity component to the total corporate-swap spread. The first parts of Panel A and B sort according to rating. We see that the fraction of spreads due to illiquidity is small for investment grade bonds, 11% or less. Using the ratio of the swap basis relative to the total spread, Longstaff, Mithal, and Neis (2005) and Han and Zhou (2008) find the fraction of spread due to liquidity at the 5-year maturity to be 2% respectively 19% consistent with our finding that it is relatively small. In speculative grade bonds the fraction due to liquidity is

24%. Post-subprime the fractions increase and range from 23 to 42 % in all ratings but *AAA* where it is only 7%. That the liquidity fractions of spreads in AAA are small in percent relative to other bonds underscores that there is a flight-to-quality effect in AAA bonds. A consistent finding from Tables 5 and 6 is that for investment grade bonds the importance of liquidity has increased after the onset of the subprime crisis both in absolute size (basis points) and relative to credit risk (fraction of spread). For speculative grade bonds the liquidity component in basis points has increased but it is stable measured as the fraction of total yield spread.

The last parts of Panel A and B in Table 6 show the liquidity fraction of total spread as a function of maturity. We introduce a fine maturity grid but do not sort according to rating in order to have a reasonable sample size in each bucket. We see that the fraction of the spread due to liquidity is small at short maturities and becomes larger as maturity increases. This is the case both pre- and post-subprime, although the fraction is higher post-subprime for all maturities. For example, post-subprime the fraction of spread due to liquidity is 43% for bonds with a maturity more than 10 years while it is 11 % for maturities less than 1 year. The fraction increases at maturities shorter than 5 years and thereafter flattens. The slight dip at the 8-10 year maturity both pre- and post subprime is due to an on-the-run effect; many bonds are issued with a maturity of 10 years and are more liquid right after issuance.[10]

We find strong differences in the pre- and post-subprime periods, and

[10]To support this claim we additionally sorted according to bond age (older and younger than 2 years). After this sort, the dip at the 8-10 year maturity was not present. Results are available on request.

in order to examine potential variation within the two periods more closely, we estimate monthly variations in liquidity and spreads as follows. Each month we a) find a regression coefficient β_t by regressing spreads on λ while controlling for credit risk, b) calculate for each bond the fraction due to illiquidity, $\frac{\beta_t(\lambda_{it}-\lambda_{5t})}{spread_{it}}$, c) find the median fraction, and d) multiply this fraction by the median spread. This gives us the total liquidity premium in basis points on a monthly basis. We do this for investment grade and speculative grade bonds separately.[11] This measures the amount of the total spread that is due to illiquidity. Figure 4 shows the time series variation in the median spread and the amount of the spread due to illiquidity.

The liquidity premium in investment grade bonds is persistent and steadily increasing during the subprime crisis and peaks in the first quarter of 2009 when stock prices decreased strongly. We see that the co-movement between the liquidity premium and credit spread is quite high. For speculative grade bonds, the liquidity premium peaks around the bankruptcy of Lehman and shows less persistence. Furthermore, the co-movement between the liquidity premium and the spread is less pronounced than for investment grade bonds, and the premium at the end of the sample period is almost down to pre-crisis levels even though the spread is still higher than before the crisis.

[11]The results become unstable if we split into finer rating categories. While the regression coefficient β_t^R can be determined reasonable well, the 5% quantile λ_{5t} becomes too noisy.

5.5 Robustness checks

In Appendix A we carry out a series of robustness checks. We test for potential endogeneity bias and find that endogeneity is not a major concern. We calculate liquidity premia using corporate bond spreads to Treasury rates instead of swap rates and find that our conclusions still hold. And we examine an alternative definition of our liquidity component and find results to be robust to this definition. We have also tried to exclude bonds with an age less than one or two years and find that our conclusions hold, a result not in the Appendix but available on request.

As a further test showing that our regression results are robust, we provide a different methodology for controlling for credit risk in this section. Longstaff, Mithal, and Neis (2005), Blanco, Brennan, and Marsh (2005), and Han and Zhou (2008) control for credit risk by assuming that the premium in a credit default swap is a pure measure of credit default risk. However, credit default swaps are shown also to contain a liquidity component (Tang and Yan (2006) and Bongaerts, Driessen, and de Jong (2009)) and this component is likely to have increased after the onset of the subprime crisis. Furthermore, only a small number of firms have actively traded credit default swaps, and those that have typically only have liquid swaps at a maturity of five years. Using credit default swaps would severely reduce our sample size.

We use an alternative approach to check our credit risk controls. The idea is that any yield spread difference between two fixed rate bullet bonds with the same maturity and issued by the same firm must be due to liquidity differences and not differences in credit risk. This intuition is formalized in the following regression.

We conduct rating-wise "paired" regressions of yield spreads on dummy variables and one liquidity measure at the time. The regression is

$$spread_{it}^{R} = dummy_{Gt}^{R} + \beta^{R} \lambda_{it}$$

where $dummy_{Gt}^{R}$ is the same for all bonds with the same rating R and approximately the same maturity. The grid of maturities is 0-0.5y, 0.5-1y, 1-3y, 3-5y, 5-7y, 7-10y, and more than 10y. For example, if firm y in quarter t has three bonds issued with maturities 5y, 5.5y, and 6y, the bonds have the same dummy in that quarter, and we assume that any yield spread difference between the bonds is due to liquidity. There are separate dummies for each quarter. Once we have dummied out credit risk in the regressions, estimated coefficients for the liquidity measure are not inconsistent because of possibly omitted credit risk variables. Hence, the paired regression is free of any endogeneity bias due to credit risk. Only groups with two or more spreads contribute to the liquidity coefficient reducing the sample compared to former regressions. Therefore, we only look at two rating groups, investment grade and speculative grade.

Table 7 shows the regression coefficients in the paired regression. We see that λ is significant in all regressions while zero trading days, the Roll measure, and turnover are only significant in some of the regressions. This supports our finding that λ is a more consistent measure of corporate bond liquidity compared to previously proposed measures.

6 Determinants of bond illiquidity

In this section, we show that our measure is also useful for analyzing other aspects of corporate bond illiquidity. Specifically, we focus on liquidity betas, the liquidity of bonds with a lead underwriter in financial distress, and the liquidity of bonds issued by financial firms relative to bonds issued by industrial firms.

6.1 Liquidity betas

We estimate bond-specific liquidity betas by calculating a monthly time series of corporate bond market illiquidity, and for each bond estimate the correlation between market-wide illiquidity and bond-specific illiquidity. The market-wide time series is calculated by averaging on a monthly basis across all observations of bond-specific λ_i using amount outstanding as weight. Bond-specific beta is estimated through the slope coefficient in the regression of bond-specific λ_i on market-wide λ, where the regression is based on all months where a bond-specific λ_i can be calculated. We calculate the betas using the whole sample period 2004Q4-2009Q2, because estimating betas separately for the pre- and post subprime periods leads to noisier estimates.

For each rating class R pooled regressions are run where yield spreads are regressed on each bonds liquidity β and our liquidity measure λ_t with credit risk controls

$$Spread_{it}^{R} = \alpha^{R} + \gamma_1^{R}\lambda_{it} + \gamma_2^{R}\beta_i + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i is for bond in rating R and t is time measured in quarter.

The result of the regression is reported in Table 8. Our regressions are run both 'marginally', i.e. with our liquidity beta as the only regressor in addition to the credit risk controls, and with our liquidity measure included as additional regressor.

Both marginally and with λ included, there is no significance pre-subprime except for the AAA-category. After the onset of the crisis, the picture changes and only spreads in the AAA-category do not depend on our liquidity beta. This is consistent with the regime-dependent importance of liquidity betas noted in Acharya, Amihud, and Bharath (2010). But whereas they use stock and Treasury bond market liquidity to measure aggregate liquidity, our measure specifically captures corporate bond market liquidity.

We saw in the previous section that the contribution to spreads of liquidity was small for AAA bonds after the onset of the crisis, and the insignificant liquidity beta coefficient for AAA in the crisis period confirms that there is a flight-to-quality effect in AAA-rated bonds.

6.2 Lead underwriter

Brunnermeier and Pedersen (2009) provide a model that links an asset's market liquidity and traders' funding liquidity, and find that when funding liquidity is tight, traders become reluctant to take on positions, especially "capital intensive" positions in high-margin securities. This lowers market liquidity. Empirical support for this prediction is found in Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) who find for equities traded on NYSE that balance sheet and income statement variables for market makers explain time variation in liquidity.

Since the TRACE data do not reveal the identity of the traders, we cannot perform direct tests of the Brunnermeier and Pedersen (2009)-model for the U.S. corporate bond market. However, if we assume that the original underwriter is more likely to make a market (as is the case in equity markets, see Ellis, Michaely, and O'Hara (2000)), we can provide indirect evidence by observing bond liquidity of bonds underwritten by Bear Stearns and Lehman Brothers, two financial institutions in distress during the subprime crisis. We therefore calculate for all bonds with Lehman Brothers as lead underwriter their average λ - weighted by amount outstanding - on a monthly basis. Likewise, we does this for bonds with Bear Stearns as lead underwriter and for all bonds in the sample. We obtain underwriter information from FISD. The results are plotted in Figure 5.

The liquidity of bonds with Bear Stearns as lead underwriter was roughly the same as an average bond entering the summer of 2007. During the week of July 16, 2007 Bear Stearns disclosed that two of their hedge funds had lost nearly all of the value, and the graph shows that the 'illiquidity gap' between Bear Stearns underwritten bonds and average bonds increased this month. On August 6, Bear Stearns said that it was weathering the worst storm in financial markets in more than 20 years, in November 2007 Bear Stearns wrote down \$1.62 billion and booked a fourth quarter loss, and in December 2007 there was a further write-down of \$1.90 billion. During these months, the 'illiquidity gap' steadily increased. Bear Stearns were in severe liquidity problems in beginning of March, and they were taken over by JPMorgan on March 16. In this month the 'illiquidity gap' peaked but returned to zero in June 2008 after Bear Stearns shareholders approved JPMorgan's buyout of the investment bank on May 29.

The liquidity of bonds underwritten by Lehman was close to the liquidity of an average bond in the market up until August 2008, but this changed in September 2008 when the 'liquidity gap' between Lehman underwritten bonds and average market bonds increased strongly in September in response to Lehman filing for bankruptcy on September 15. The gap stayed at high levels during the rest of the sample period suggesting that after the Lehman default, bonds they had underwritten became permanently more illiquid.

6.3 Industry

Bonds issued by financial firms might by more or less liquid compared to bonds issued by industrial firms. They might be less liquid because financial firms are more opaque, especially in times of financial distress, and their bonds might be more affected by asymmetric information. They might be more liquid because financial firms are more connected to capital markets and are liquidity providers to the market.

The empirical evidence is mixed. Longstaff, Mithal, and Neis (2005) find in a study of 68 bonds that bonds issued by financial firms are more illiquid and command a higher liquidity premium. In contrast, Friewald, Jankowitsch, and Subrahmanyam (2009) find that there is no difference, except during the subprime crisis where bonds of financial firms are in fact more liquid.

We address the issue by calculating a value-weighted average monthly illiquidity λ of financial respectively industrial firms and plotting the time series behavior in Figure 6. We obtain bond industry from FISD. In general, there is little systematic difference. For both financial and industrial bonds, illiquidity goes up at the onset of the crisis. There are, however, additional spikes in illiquidity for financial firms around the takeover of Bear Stearns in March 2008, around the Lehman bankruptcy in September 2008, and around the stock market decline in the first quarter of 2009. That is, in times of severe financial distress, illiquidity of financial bonds increases relative to that of industrial bonds, while in other times illiquidity is similar.

By calculating monthly averages, we are able to draw more high-frequency inferences compared to other papers, since averaging λ over longer periods of time, the approach taken in Longstaff, Mithal, and Neis (2005) and Friewald, Jankowitsch, and Subrahmanyam (2009), would wash out the effects we see.

7 Conclusion

The subprime crisis dramatically increased corporate bond spreads and while default risk certainly has increased because of funding constraints and the slowing of the real economy, it is also widely believed that deteriorating liquidity has contributed to the widening of spreads. The difficulty is how to measure this contribution.

In this paper, we show that an equally weighted sum of four (normalized) measures of liquidity and liquidity risk consistently contributes to corporate bond spreads across time and across ratings. The four measures are the Amihud measure of price impact, a measure of roundtrip trading costs and the variability of these two measures. The equally weighted sum is a close approximation to the first factor in a principal component analysis of eight liquidity measures, and this is true both before and after the onset of the crisis. Our measure dominates other liquidity measures, such as the Roll measure and zero trading days.

The measure is used to analyze the contribution of illiquidity to corporate bond spreads before and after the onset of the subprime crisis. We find that before the crisis, the contribution to spreads from illiquidty was small for investment grade bonds both measured in basis points and as a fraction of total spreads. The contribution increased strongly at the onset of the crisis for all bonds except AAA-rated bonds, which is consistent with a flight-to-quality into AAA-rated bonds. Liquidity premia in investment grade bonds rose steadily during the crisis and peaked when the stock market declined strongly in the first quarter of 2009, while premia in speculative grade bonds peaked during the Lehman default and returned almost to pre-crisis levels in mid-2009. The number of zero trading days did not increase with the crisis and we find evidence that this was because trades in less liquid bonds were split into trades of smaller size.

Our measure is useful for analyzing other important aspects of corporate bond liquidity. From the covariation between an individual bond's liquidity measure and a value-weighted average of all bonds' liquidity measures, we define a liquidity beta which is shown to have little effect on spreads before the onset of the crisis, but does have a positive effect for all bonds except AAA-bonds after the crisis. This is consistent with the regime-dependent role of liquidity betas found in Acharya, Amihud, and Bharath (2010) but it narrows the flight-to-quality story from general investment grade bonds to AAA-rated bonds only.

We also use our measure to study the impact on bond liquidity of funding shocks to lead underwriters and to compare illiquidity of corporate bonds issued by financial firms with that of industrial firms. Financial distress of lead underwriters clearly affects the liquidity of the bonds for which they have served as lead underwriters. Bonds issued by financial firms are not permanently more or less liquid than industrials but they do, however, have illiquidity spikes around the take-over of bear Sterns, the collapse of Lehman and the March 2009 rapid stock market decline.

References

Acharya, V., Y. Amihud, and S. Bharath (2010). Liquidity Risk of Corporate Bond Returns. Working Paper. New York University.

Acharya, V. V. and L. H. Pedersen (2005). Asset Pricing with Liquidity Risk. *Journal of Financial Economics 77*(2), 375–410.

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets 5*(1), 31–56.

Amihud, Y., H. Mendelson, and L. H. Pedersen (2005). Liquidity and Asset Prices. *Foundations and Trends in Finance 1*(4), 269–364.

Bao, J., J. Pan, and J. Wang (2009). Liquidity of Corporate Bonds. Working Paper. MIT Sloan School of Management.

Bessembinder, H., W. Maxwell, and K. Venkaraman (2006). Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds. *Journal of Financial Economics 82*(2), 251–288.

Blanco, R., S. Brennan, and I. W. Marsh (2005). An Empirical Analysis of the Dynamic Relationship between Investment Grade Bonds and Credit Default Swaps. *Journal of Finance 60*(5), 2255–2281.

Blume, M. E., F. Lim, and A. C. MacKinlay (1998). The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality? *Journal of Finance 53*(4), 1389–1401.

Bongaerts, D., J. Driessen, and F. de Jong (2009). Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market. Forthcoming, Journal of Finance.

Brunnermeier, M. and L. Pedersen (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies 22*, 2201–2238.

Cameron, C., J. Gelbach, and D. Miller (2008). Bootstrap-Based Improvements for Inference with Clustered Errors. *Review of Economic Studies 90*(3), 414–427.

Chen, L., D. Lesmond, and J. Wei (2007). Corporate Yield Spreads and Bond Liquidity. *Journal of Finance 62*(1), 119–149.

Collin-Dufresne, P., R. S. Goldstein, and J. Martin (2001). The determinants of credit spread changes. *Journal of Finance 56*, 2177–2207.

Comerton-Forde, C., T. Hendershott, C. M. Jones, P. C. Moulton, and M. S. Seasholes (2010). Time variation in liquidity: the role of market-maker inventories and revenues. *Journal of Finance 65*(1), 295–332.

Constantinides, G. (1986). Capital Market Equilibrium with Transaction Costs. *Journal of Political Economy 94*, 842–862.

Covitz, D. and C. Downing (2007). Liquidity or Credit Risk? The Determinants of Very Short-Term Corporate Yield Spreads. *Journal of Finance 62*(5), 2303–2328.

Davidson, R. and J. G. MacKinnon (1993). *Estimation and Inference in Econometrics*. New York, Oxford University Press.

de Jong, F. and J. Driessen (2006). Liquidity Risk Premia in Corporate Bond Markets. Working Paper. Tilburg University and University of Amsterdam.

Dick-Nielsen, J. (2009). Liquidity biases in TRACE. *Journal of Fixed Income 19*(2), 43–55.

Downing, C., S. Underwood, and Y. Xing (2005). Is Liquidity Risk Priced in the Corporate Bond Market? *Working Paper, Rice University*.

Duffie, D. and D. Lando (2001, May). Term structures of credit spreads with incomplete accounting information. *Econometrica 69*(3), 633–664.

Edwards, A. K., L. E. Harris, and M. S. Piwowar (2007). Corporate Bond Market Transaction Cost and Transparency. *Journal of Finance 62*(3), 1421–1451.

Ellis, K., R. Michaely, and M. O'Hara (2000). When the underwriter is the market maker: an examination of trading in the IPO aftermarket. *Journal of Finance 55*(3), 1039–1074.

Elton, E., M. Gruber, D. Agrawal, and C. Mann (2001). Explaining the Rate Spread on Corporate Bonds. *Journal of Finance 56*(1), 247–277.

Ericsson, J. and O. Renault (2006). Liquidity and Credit Risk. *Journal of Finance 61*(5), 2219–2250.

Feldhütter, P. (2010). The same bond at different prices: identifying search frictions and selling pressures. *Working Paper, Copenhagen Business School*.

Feldhütter, P. and D. Lando (2008). Decomposing Swap Spreads. *Journal of Financial Economics 88*, 375–405.

Friewald, N., R. Jankowitsch, and M. G. Subrahmanyam (2009). Illiquidity or credit deterioration: a study of liquidity in the US corporate bond market during financial crises. Working Paper.

Güntay, L. and D. Hackbarth (2006). Liquidity of Corporate Bond Credit

Spreads and Forecast Dispersion. Working Paper. Available at SSRN: http://ssrn.com/abstract=891698.

Goldstein, M. A. and E. Hotchkiss (2008). Dealer Behavior and the Trading of Newly Issued Corporate Bonds. *Working Paper*.

Goldstein, M. A., E. S. Hotchkiss, and E. R. Sirri (2007). Transparency and Liquidity: A Controlled Experiment on Corporate Bonds. *The Review of Financial Studies 20*(2), 235–273.

Green, R., B. Hollifield, and N. Schürhoff (2007). Financial Intermediation and the Costs of Trading in an Opaque Market. *Review of Financial Studies 20*(2), 275–314.

Han, S. and H. Zhou (2008). Effects of Bond Liquidity on the Nondefault Component of Corporate Bond Spreads: Evidence from Intraday Transactions Data. *Working Paper, Federal Reserve Board*.

Harris, L. (1990). Statistical Properties of the Roll Serial Covariance Bid/Ask Spread Estimator. *Journal of Finance 45*(2), 579–590.

Houweling, P., A. Mentink, and T. Vorst (2005). Comparing Possible Proxies of Corporate Bond Liquidity. *Journal of Banking and Finance 29*(6), 1331–1358.

Huang, J. and M. Huang (2003). How Much of the Corporate-Treasury Yield Spread is due to Credit Risk? *Working Paper, Stanford University*.

Huberman, G. and W. Stanzl (2005). Optimal Liquidity Trading. *Review of Finance 9*, 165–200.

Hull, J., M. Predescu, and A. White (2004). The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. *Journal of Banking and Finance 28*, 2789–2811.

Johnson, T. C. (2008). Volume, liquidity, and liquidity risk. *Journal of Financial Economics 87*, 388–417.

Kyle, A. S. (1985). Continuous Auctions And Insider Trading. *Econometrica 53*(6), 1315–1334.

Longstaff, F., S. Mithal, and E. Neis (2005). Corporate yield spreads: default risk or liquidity? New evidence from the credit-default swap market. *Journal of Finance 60*(5), 2213–2253.

Mahanti, S., A. Nashikkar, M. Subramanyam, G. Chacko, and G. Mallik (2008). Latent Liquidity: A New Measure of Liquidity with an Application to Corporate Bonds. *Journal of Financial Economics 88*, 272–298.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies 22*(1), 435–480.

Roll, R. (1984). A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *Journal of Finance 39*(2), 1127–1139.

Sarig, O. and A. Warga (1989). Bond Price Data and Bond Market Liquidity. *Journal of Financial and Quantitative Analysis 24*(3), 367–378.

Tang, D. Y. and H. Yan (2006). Liquidity, Liquidity Spillover, and Credit Default Swap Spreads. *Working Paper*.

Appendix A Robustness checks

In this Appendix we discuss possible misspecification in our regression analysis. We test for endogeneity, show that our results are robust to the choice of benchmark riskfree rate, and show that results are robust to how we define the liquidity component.

A.1 Endogeneity

There may be a two way causal relationship between contemporaneous measures of liquidity and credit risk and failing to account for such a relationship in regressions results in inconsistent OLS estimates. This simultaneity bias is not a concern in our regressions since liquidity measures lag our measure of credit spreads. Spreads are measured on the last day in each quarter while liquidity measures are based on transactions during the quarter, so liquidity measures are lagged in time relative to spreads.

To test for potential endogeneity bias, we use a residual augmented two stage least squares t-test as in Davidson and MacKinnon (1993), equivalent to the Durbin-Wu-Hausman test. We do this for every marginal regression in Table 2, that is, test every liquidity variable separately. If the test is not significant the liquidity variable can be regarded as exogenous. As instrument we use bond age and therefore exclude it in the yield spread regressions[12]. Table 9 shows the R^2's for the first stage regressions and the t-statistic tests for endogeneity. Most R^2's are relatively high indicating that the control

[12] Another potential instrument is amount issued. Since this variable is significant in most of the regressions in Table 4, omitting it from the regressions in the test creates a new endogeneity problem. The tests in this case would likely show an endogeneity problem even if it is not there, and if we use amount issued as instrument, this is indeed the case.

variables including the instrument are able to explain a large portion of the variation in the liquidity measures. Out of the 80 test statistics 80% are insignificant at a 10% level indicating that endogeneity is not a major concern.

A.2 Benchmark riskfree rate

The size of the nondefault component in corporate bond spreads investigated by among others Huang and Huang (2003) and Longstaff, Mithal, and Neis (2005) depend strongly on the chosen riskfree rate. In Longstaff, Mithal, and Neis (2005) the difference is around 60 basis points. As Table 10 shows the estimated liquidity component when the Treasury rate is used as riskfree rate instead of the swap rate does not change much. The change in estimated liquidity is often less than one basis point and is for all rating categories less than 10 basis points. Therefore, our findings on the size of the liquidity premium in basis points are insensitive to the choice of benchmark (while our findings on the fraction out of the total spread of course depend on the benchmark riskfree rate).

A.3 Alternative definition of liquidity component

The liquidity component is calculated as the the median minus 5% quantile of the liquidity score and has the natural interpretation as the liquidity premium of an average bond in the corporate bond market relative to a very liquid bond. To check that our main results are robust to the definition of the liquidity component, Table 11 shows the liquidity component when it is defined as the 75% quantile minus 5% quantile. The component in this table can be interpreted as that of an illiquid bond relative to a very liquid bond. Table 11 shows that the liquidity component is larger for an illiquid bond compared to an average bond (which by definition must the case). Also, Table 11 shows that the main results of the paper are unchanged: liquidity premia are increasing in maturity, the liquidity premium is higher post-subprime compared to pre-subprime, and the liquidity premium for investment grade bonds is small pre-subprime.

Panel A: Summary statistics for liquidity proxies

	Amihud	Roll	firm zero	bond zero	turnover	URC	Amihud risk	URC risk
99th	0.0813	8.39	92.1	96.8	0.247	0.0156	0.1592	0.01702
95th	0.0427	3.16	76.2	93.5	0.136	0.0096	0.0792	0.00997
75th	0.0120	1.05	12.5	79.7	0.070	0.0041	0.0298	0.00427
50th	0.0044	0.53	0.0	60.7	0.045	0.0022	0.0147	0.00220
25th	0.0015	0.29	0.0	31.7	0.028	0.0012	0.0064	0.00102
5th	0.0003	0.12	0.0	6.3	0.012	0.0005	0.0011	0.00024
1st	0.0000	0.06	0.0	0.0	0.005	0.0002	0.0002	0.00003

Panel B: Correlation matrix for liquidity proxies

	Amihud	Roll	firm zero	bond zero	turnover	URC	Amihud risk	URC risk
Amihud	1.00							
Roll	0.16	1.00						
firm zero	−0.08	0.11	1.00					
bond zero	−0.08	0.18	0.46	1.00				
turnover	−0.20	0.04	0.03	0.04	1.00			
URC	0.72	0.20	−0.03	−0.03	−0.13	1.00		
Amihud risk	0.61	0.10	−0.12	−0.12	−0.11	0.69	1.00	
URC risk	0.57	0.14	−0.12	−0.19	−0.11	0.87	0.69	1.00

Table 1: Statistics for liquidity proxies. This table shows statistics for corporate bond liquidity proxies. The proxies are described in detail in Section 4 and are calculated quarterly from 2004:Q4 to 2009:Q2. Panel A shows quantiles for the proxies. Panel B shows correlations among the proxies. There is a total of 2,224 bond issues and 380 bond issuers in our sample.

Panel A: Marginal liquidity regressions, pre-subprime (2004:Q4-2007:Q1)

	AAA	AA	A	BBB	spec
Amihud	1.15***	2.08***	4.14***	3.68	14.12
	(4.87)	(3.85)	(3.18)	(1.52)	(1.63)
Roll	0.02***	0.02***	0.01	0.02	0.05
	(3.18)	(3.48)	(1.48)	(0.53)	(1.26)
firm zero	0.000	−0.001	0.000	−0.001*	−0.005
	(0.46)	(−1.42)	(0.74)	(−1.66)	(−1.60)
bond zero	−0.000	−0.000	0.000	−0.003**	−0.012**
	(−0.09)	(−0.86)	(1.13)	(−2.22)	(−2.33)
turnover	−0.27***	−0.12	−0.03	−0.03	−0.05
	(−6.52)	(−0.97)	(−0.31)	(−0.18)	(−0.09)
URC	3.83**	7.11***	18.91***	47.47***	69.29**
	(2.03)	(2.66)	(2.61)	(3.76)	(2.26)
Amihud risk	0.39*	0.55*	1.43**	3.46***	9.48**
	(1.82)	(1.87)	(2.42)	(3.46)	(2.29)
URC risk	2.08**	3.98*	9.16**	25.99***	57.20***
	(2.30)	(1.95)	(2.29)	(3.18)	(3.67)

Panel B: Marginal liquidity regressions, post-subprime (2007:Q2-2009:Q2)

	AAA	AA	A	BBB	spec
Amihud	2.93***	18.40***	6.80	21.94**	22.47
	(2.98)	(2.94)	(0.82)	(2.54)	(1.52)
Roll	0.04***	−0.02	0.04	0.19*	−0.73
	(2.58)	(−1.55)	(0.87)	(1.76)	(−1.47)
firm zero	−0.016	−0.000	−0.000	−0.023**	−0.047**
	(−1.46)	(−0.03)	(−0.07)	(−2.22)	(−2.05)
bond zero	0.007***	0.002	0.013**	−0.016	−0.087
	(7.26)	(0.73)	(2.31)	(−0.53)	(−1.49)
turnover	−2.95***	−2.12	−0.74	−2.97	14.47
	(−11.87)	(−1.11)	(−0.31)	(−0.33)	(0.82)
URC	20.50***	191.63***	209.47***	212.15***	−143.70
	(2.88)	(3.08)	(4.74)	(2.96)	(−0.57)
Amihud risk	1.99	18.87***	20.66***	21.42**	24.11**
	(1.25)	(4.74)	(3.26)	(2.22)	(2.43)
URC risk	17.40**	167.60***	190.46***	270.28***	233.16**
	(2.07)	(3.71)	(4.03)	(4.23)	(2.13)

Table 2: Marginal liquidity regressions. For each rating class R and each liquidity variable L a pooled regression is run with credit risk controls

$$Spread_{it}^R = \alpha^R + \gamma^R L_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i is for bond in rating R and t is time measured in quarter. In total 40 regressions are run (8 liquidity variables $\times$ 5 rating classes). This table shows for each regression the coefficient and t-statistics in parenthesis for the liquidity variable, γ. The proxies are described in detail in Section 4 and are calculated quarterly from $2004:Q4$ to $2009:Q2$. Panel A shows the coefficients using data before the subprime crisis, while Panel B shows the coefficients using data after the onset of the subprime crisis. Standard errors are corrected for time series effects, firm fixed effects, and heteroscedasticity, and significance at 10% level is marked '*', at 5% marked '**', and at 1% marked '***'.

Panel A: Principal Component loadings, pre-subprime (2004:Q4-2007:Q1)

	1PC	2PC	3PC	4PC	5PC	6PC	7PC	8PC
Amihud	0.45	0.05	−0.12	−0.05	0.44	0.70	−0.12	0.28
Roll	0.26	0.33	0.08	−0.86	−0.27	−0.06	0.06	0.02
firm zero	−0.04	0.64	−0.02	0.39	−0.56	0.36	0.07	0.02
bond zero	−0.00	0.67	−0.10	0.10	0.56	−0.45	0.05	0.11
turnover	−0.02	0.07	0.98	0.07	0.15	0.08	0.01	0.03
URC	0.52	0.06	0.03	0.15	0.00	−0.10	−0.39	−0.73
Amihud risk	0.47	−0.11	0.01	0.16	−0.01	−0.09	0.85	−0.09
URC risk	0.49	−0.12	0.06	0.21	−0.29	−0.40	−0.31	0.60
cum. % explained	39%	59%	72%	81%	89%	94%	99%	100%

Panel B: Principal Component loadings, post-subprime (2007:Q2-2009:Q2)

	1PC	2PC	3PC	4PC	5PC	6PC	7PC	8PC
Amihud	0.46	0.04	−0.10	−0.10	−0.07	0.73	0.43	0.21
Roll	0.06	0.47	0.35	−0.78	0.10	−0.02	−0.17	0.02
firm zero	−0.11	0.59	−0.28	0.33	0.62	0.20	−0.17	0.00
bond zero	−0.12	0.64	−0.07	0.21	−0.67	−0.16	0.21	0.12
turnover	−0.14	0.05	0.88	0.39	0.08	0.20	0.12	0.01
URC	0.52	0.15	0.06	0.09	0.09	−0.26	0.28	−0.73
Amihud risk	0.46	0.03	0.07	0.21	−0.30	0.19	−0.78	−0.04
URC risk	0.51	0.02	0.09	0.13	0.23	−0.51	0.10	0.63
cum. % explained	39%	58%	71%	81%	88%	94%	99%	100%

Table 3: Principal component loadings on the liquidity variables. This table shows the principal component analysis loadings on each of the eight liquidity variables along with the cumulative explanatory power of the components.

Panel A: Multivariate liquidity regressions, pre-subprime (2004:Q4-2007:Q1)

	AAA	AA	A	BBB	spec
intercept	−0.4	0.2	−0.5	2.2***	−0.1
	(−1.24)	(1.20)	(−1.62)	(2.84)	(−0.03)
1PCA	0.01***	0.02***	0.03***	0.05***	0.30***
	(3.22)	(12.31)	(3.28)	(2.88)	(5.65)
2PCA	0.01	−0.00	0.04***	−0.06	−0.19
	(0.58)	(−0.09)	(3.41)	(−1.30)	(−1.19)
3PCA	−0.014***	−0.006	0.018***	−0.005	0.093
	(−4.20)	(−0.72)	(2.66)	(−0.21)	(0.88)
4PCA	−0.020**	−0.022***	−0.002	−0.015	0.112*
	(−2.32)	(−2.94)	(−0.18)	(−0.67)	(1.92)
5PCA	0.00	0.02***	0.03*	−0.05	−0.02
	(0.01)	(3.08)	(1.88)	(−1.22)	(−0.16)
6PCA	0.00	0.01	0.03***	0.03	0.24*
	(0.69)	(0.81)	(4.19)	(0.65)	(1.91)
7PCA	0.00	−0.00	−0.00	−0.02*	−0.10*
	(0.27)	(−0.28)	(−0.55)	(−1.70)	(−1.68)
8PCA	0.02***	0.02	−0.01	−0.23***	−0.17
	(3.07)	(1.43)	(−0.74)	(−2.58)	(−1.56)
age	0.00	−0.00	0.00	−0.01	−0.00
	(0.08)	(−0.96)	(1.12)	(−1.26)	(−0.12)
amount issued	−0.025***	−0.012	0.032**	−0.108***	−0.143
	(−3.52)	(−1.34)	(2.57)	(−2.65)	(−0.87)
forecast dispersion	3.05	0.02	0.73**	0.65**	1.21
	(1.64)	(1.30)	(2.12)	(2.04)	(1.37)
coupon	0.02**	0.02***	0.01*	0.07***	0.29***
	(1.99)	(4.00)	(1.79)	(4.46)	(3.62)
10y swap	−0.05*	−0.03***	−0.05***	−0.06***	−0.26
	(−1.82)	(−3.76)	(−4.23)	(−4.03)	(−1.33)
10y-2y swap	0.005	−0.030**	−0.020***	−0.107***	−0.132
	(0.79)	(−2.28)	(−2.89)	(−5.31)	(−0.44)
equity vol	−0.002	0.008***	0.006*	0.011***	0.093***
	(−0.33)	(15.21)	(1.68)	(4.17)	(5.88)
pretax1	0.344***	0.023***	0.010	−0.026	0.027
	(3.53)	(2.88)	(0.57)	(−1.36)	(0.44)
pretax2	−0.051***	−0.016***	−0.011*	−0.013	−0.068
	(−3.06)	(−4.90)	(−1.90)	(−1.54)	(−0.90)
pretax3	−0.007	0.000	−0.001	0.011**	0.048
	(−1.00)	(0.18)	(−0.35)	(2.18)	(0.95)
pretax4	−0.003***	0.000	0.000	−0.005***	−0.022
	(−3.78)	(0.03)	(0.26)	(−3.31)	(−1.30)
sales to income	−0.002	−0.000	−0.000	−0.005**	−0.003**
	(−1.14)	(−0.53)	(−0.01)	(−2.14)	(−1.97)
long term debt to asset	−0.016**	−0.002***	0.001	0.008***	−0.001
	(−2.49)	(−4.13)	(1.16)	(2.92)	(−0.02)
leverage ratio	0.009***	0.001	−0.001	0.000	0.023
	(3.04)	(1.58)	(−1.00)	(0.10)	(0.91)
time-to-maturity	0.016***	0.019***	0.022***	0.040***	0.043***
	(3.50)	(18.21)	(15.21)	(7.95)	(2.99)
N	533	1869	4148	1340	1075
R^2	0.46	0.53	0.47	0.60	0.61

Table 4: Multivariate liquidity regressions. For each of the five rating classes a pooled regression with quarterly observations is run with variables measuring both liquidity and credit risk. Panel A shows the regression coefficients and t-statistics in parenthesis when using data from 2004:Q4 to 2007:Q1, while Panel B shows the results for data from 2007:Q2 to 2009:Q2. Standard errors are corrected for time series effects, firm fixed effects, and heteroscedasticity, and significance at 10% level is marked '*', at 5% marked '**', and at 1% marked '***'.

Panel B: Multivariate liquidity regressions, post-subprime (2007:Q2-2009:Q2)					
	AAA	AA	A	BBB	spec
intercept	-2.5^{**}	-2.6	1.0^{***}	24.9	30.2^{*}
	(-2.00)	(-1.00)	(2.66)	(1.42)	(1.65)
1PCA	0.05^{*}	0.48^{***}	0.45^{***}	0.67^{***}	1.16^{***}
	(1.91)	(4.50)	(4.64)	(3.18)	(4.33)
2PCA	-0.08	0.15	0.26^{**}	-0.03	-0.73
	(-0.57)	(1.60)	(2.27)	(-0.05)	(-1.21)
3PCA	0.066	0.153^{***}	0.146^{***}	0.389^{*}	0.349
	(1.21)	(2.96)	(3.27)	(1.75)	(0.90)
4PCA	-0.125	0.283^{***}	0.267^{***}	0.110^{*}	0.900
	(-1.35)	(5.14)	(4.07)	(1.81)	(1.40)
5PCA	-0.35^{***}	-0.18	-0.17^{***}	-0.46	0.52
	(-2.75)	(-1.17)	(-7.65)	(-0.90)	(0.97)
6PCA	-0.09^{*}	-0.17	-0.41^{*}	-0.30^{*}	1.00^{**}
	(-1.76)	(-1.30)	(-1.67)	(-1.70)	(2.57)
7PCA	0.07	-0.39^{*}	-0.22	-0.44	-0.58^{**}
	(0.68)	(-1.79)	(-1.24)	(-1.08)	(-1.98)
8PCA	0.12^{*}	0.07	-0.29^{**}	1.04	0.63
	(1.72)	(0.30)	(-2.14)	(1.11)	(0.54)
age	-0.03^{***}	-0.02	0.02	0.10	0.18^{***}
	(-4.83)	(-0.84)	(0.52)	(1.02)	(3.12)
amount issued	0.087^{***}	0.101	0.009	-0.715	-0.571
	(4.22)	(1.27)	(0.09)	(-1.04)	(-0.72)
forecast dispersion	18.32^{***}	0.13^{***}	0.15^{***}	0.76^{***}	1.06^{***}
	(3.07)	(3.75)	(3.34)	(7.31)	(4.31)
coupon	0.10^{***}	0.10^{**}	0.02	-0.50	-0.09
	(4.46)	(2.07)	(0.17)	(-1.34)	(-0.19)
10y swap	-0.32^{***}	0.07	-0.09	-1.33^{***}	-3.18^{***}
	(-6.18)	(0.24)	(-0.22)	(-3.25)	(-3.05)
10y-2y swap	-0.400^{**}	-0.490	-0.820^{*}	-0.962	-1.962^{***}
	(-2.17)	(-1.58)	(-1.95)	(-1.23)	(-2.59)
equity vol	0.096^{***}	0.055^{***}	0.050^{***}	0.050^{***}	0.097^{***}
	(6.22)	(3.82)	(3.64)	(3.06)	(3.24)
pretax1	-0.836^{**}	0.004	-0.098^{*}	-0.051	0.001
	(-2.17)	(0.21)	(-1.80)	(-0.53)	(0.44)
pretax2	0.422^{***}	0.033	-0.000	-0.073	-0.442
	(5.33)	(0.93)	(-0.00)	(-0.53)	(-0.53)
pretax3	0.144	-0.041^{***}	-0.003	0.076	0.000
	(0.78)	(-2.59)	(-0.37)	(0.81)	(NaN)
pretax4	0.003	0.052^{*}	0.008	-0.067	0.000
	(0.65)	(1.83)	(0.50)	(-0.62)	(NaN)
sales to income	-0.108^{*}	-0.003^{***}	-0.001^{***}	-0.002^{***}	-0.013
	(-1.68)	(-4.56)	(-3.79)	(-7.81)	(-1.25)
long term debt to asset	-0.256^{***}	-0.009	0.044^{**}	0.058	-0.108^{***}
	(-2.67)	(-0.71)	(2.40)	(1.56)	(-4.57)
leverage ratio	0.184^{*}	0.000	-0.026^{***}	-0.005	0.106^{***}
	(1.92)	(0.00)	(-3.55)	(-0.17)	(13.08)
time-to-maturity	0.024^{***}	-0.015	-0.035^{*}	-0.064	-0.124^{***}
	(6.00)	(-0.96)	(-1.72)	(-1.43)	(-2.63)
N	414	1549	2533	539	464
R^2	0.84	0.71	0.67	0.79	0.72

Table 4: continued.

Panel A: Liquidity component in basis points, pre-subprime (2004Q4-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	0.8	0.6 (0.3;0.8)	0.9 (0.5;1.3)	1.1 (0.6;1.5)	162	178	193
AA	1.0	0.7 (0.3;1.1)	1.0 (0.4;1.7)	1.3 (0.5;2.2)	704	667	498
A	2.4	1.5 (0.6;2.3)	2.5 (1.1;3.9)	3.2 (1.4;4.9)	1540	1346	1260
BBB	3.9	2.8 (1.4;4.4)	4.0 (1.9;6.2)	4.7 (2.3;7.3)	517	270	553
spec	57.6	45.0 (32.3;57.4)	44.0 (31.5;56.0)	83.9 (60.2;106.8)	270	324	480

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2009:Q2)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	4.9	2.5 (0.5;4.4)	4.5 (0.9;8.0)	7.9 (1.7;14.1)	110	149	155
AA	41.8	23.5 (12.9;33.2)	37.1 (20.3;52.4)	64.7 (35.5;91.4)	493	572	483
A	50.7	26.6 (15.3;39.2)	51.0 (29.3;75.1)	74.5 (42.9;109.7)	762	878	890
BBB	92.7	64.3 (36.5;92.7)	115.6 (65.6;166.6)	98.1 (55.7;141.4)	123	159	256
spec	196.8	123.6 (80.2;157.3)	224.0 (145.3;285.1)	242.7 (157.4;308.8)	133	129	201

Table 5: Liquidity Component in basis points. For each rating R we run the pooled regression

$$spread_{it}^{R} = \alpha^{R} + \beta^{R}\lambda_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i refers to bond, t to time, and λ_{it} is our liquidity measure. The bond spread is measured with respect to the swap rate. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we sort increasingly all values of λ_{it} and find the median value λ_{50} and the 5% value λ_5. The liquidity component in the bucket is defined as $\beta(\lambda_{50} - \lambda_5)$. This table shows for all buckets the liquidity component with standard errors in parenthesis. Confidence bands are found by a wild cluster bootstrap.

Panel A: Liquidity component in fraction of spread, pre-subprime (2005:Q1-2007:Q1)

rating	AAA	AA	A	BBB	spec
fraction in pct	3	4	11	8	24
	(2;5)	(2;7)	(5;18)	(3;12)	(18;30)
N	533	1869	4148	1340	1075

maturity	0-1y	1-2y	2-3y	3-4y	4-5y	5-8y	8-10y	10-30y
fraction in pct	3	7	13	13	13	11	8	10
	(2;4)	(4;9)	(8;17)	(8;18)	(8;17)	(7;15)	(5;11)	(7;14)
N	1596	1613	1241	891	641	1187	578	1218

Panel B: Liquidity component in fraction of spread, post-subprime (2007:Q2-2009:Q2)

rating	AAA	AA	A	BBB	spec
fraction in pct	7	42	26	29	23
	(1;12)	(23;60)	(14;39)	(16;41)	(16;30)
N	414	1549	2533	539	464

maturity	0-1y	1-2y	2-3y	3-4y	4-5y	5-8y	8-10y	10-30y
fraction in pct	11	20	23	27	31	44	33	43
	(7;14)	(13;27)	(15;31)	(18;38)	(20;42)	(28;60)	(21;44)	(28;53)
N	809	819	675	657	556	817	568	598

Table 6: Liquidity component in fraction of spread. For each rating R we run the pooled regression

$$spread_{it}^{R} = \alpha^{R} + \beta^{R}\lambda_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i refers to bond, t to time, and λ_{it} is our liquidity measure. Within each rating we sort increasingly all values of λ_{it} and find the 5% value λ_5. For each bond we define the liquidity fraction of the total spread as $\frac{\beta^R(\lambda_{it}-\lambda_5)}{spread_{it}^R}$. The estimated fractions in the table are for each entry the median fraction. Confidence bands are found by a wild cluster bootstrap.

	pre-subprime		post-subprime	
	investment	spec	investment	spec
λ	0.01^{***}	0.09^{**}	0.12^{***}	0.41^{*}
	(3.79)	(2.43)	(3.58)	(1.95)
Amihud	2.26^{***}	16.80^{***}	16.10^{***}	54.65
	(5.11)	(3.51)	(3.04)	(1.54)
Roll	0.03^{***}	0.16^{**}	0.05^{**}	0.39
	(3.56)	(2.54)	(2.14)	(1.44)
bond zero	0.00^{***}	0.01^{**}	0.00	0.03
	(5.85)	(2.28)	(0.78)	(1.12)
turnover	0.11^{*}	1.48^{*}	-3.21	72.74
	(1.87)	(1.72)	(-1.46)	(1.63)
URC	8.48^{***}	125.03^{**}	104.34^{**}	-95.04
	(3.72)	(2.55)	(2.43)	(-0.58)
URC risk	1.30	57.15^{**}	39.09^{***}	-103.42
	(0.69)	(2.15)	(2.97)	(-0.74)
Amihud risk	0.64^{***}	9.44^{***}	6.56^{***}	39.63^{***}
	(4.21)	(2.79)	(3.19)	(4.60)

Table 7: Paired regression. We pair bonds from the same firm with similar maturity and regress their yield spreads on liquidity variables one at a time and add a dummy for a given firm and maturity combination. Since bonds with similar maturity and issued by the same firm have similar credit risk characteristics, the dummy controls for credit risk. Significance at 10% level is marked '*', at 5% marked '**', and at 1% marked '***'.

	pre-subprime		post-subprime	
	β	λ	β	λ
AAA	-0.0034		-0.0085	
	(-1.34)		(-0.84)	
	-0.0056^{***}	0.0033^{***}	0.0159	0.0234^{**}
	(-3.26)	(2.65)	(1.26)	(2.38)
AA	0.0012		0.1823^{*}	
	(0.23)		(1.94)	
	0.0067	0.0017	0.1720^{**}	0.1712^{***}
	(1.06)	(0.60)	(2.14)	(3.82)
A	-0.0004		0.2631^{**}	
	(-0.14)		(2.22)	
	0.0021	0.0106^{**}	0.2314^{**}	0.1211^{**}
	(0.65)	(2.57)	(2.15)	(2.03)
BBB	0.0044		0.2171^{***}	
	(1.34)		(4.05)	
	0.0012	0.0254^{***}	0.3187^{***}	0.3242^{***}
	(0.34)	(4.33)	(3.44)	(2.91)
spec	0.0102		1.3538^{***}	
	(0.90)		(2.60)	
	0.0162	0.1502^{***}	1.3140^{**}	0.4155^{***}
	(1.31)	(4.64)	(2.73)	(7.08)

Table 8: β regressions. For each rating class R pooled regressions are run where yield spreads are regressed on each bonds liquidity β and our liquidity measure λ_t with credit risk controls

$$Spread_{it}^{R} = \alpha^{R} + \gamma_1^{R}\lambda_{it} + \gamma_2^{R}\beta_i + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i is for bond in rating R and t is time measured in quarter. Each bond's β_i is calculated as the covariance between this bond's monthly λ_{it} and a size-weighted monthly market λ_{Mt}. Two regressions for each rating pre- and post-subprime are run; one with only β included and one with both β and λ included. Standard errors are corrected for time series effects, firm fixed effects, and heteroscedasticity, and significance at 10% level is marked '*', at 5% marked '**', and at 1% marked '***'.

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Panel A: Endogeneity tests, pre-subprime (2004:Q4-2007:Q1)

	AAA	AA	A	BBB	spec
Amihud	-0.43	-1.00	0.98	1.31	0.71
	(33%)	(20%)	(18%)	(9%)	(34%)
Roll	0.66	-0.98	0.98	1.16	-0.45
	(47%)	(30%)	(32%)	(24%)	(25%)
firm zero	-0.25	1.08	-0.83	-1.18	0.27
	(88%)	(34%)	(23%)	(25%)	(46%)
bond zero	-0.41	1.04	-0.69	0.85	-0.87
	(83%)	(67%)	(68%)	(45%)	(61%)
turnover	-0.18	-1.13	0.86	-1.05	1.04
	(19%)	(28%)	(15%)	(29%)	(39%)
URC	0.51	-1.08	0.95	1.45	0.13
	(34%)	(18%)	(19%)	(23%)	(37%)
Amihud risk	0.45	-1.09	0.89	1.43	0.31
	(19%)	(10%)	(11%)	(13%)	(31%)
URC risk	0.46	-1.08	0.90	1.29	-0.03
	(13%)	(12%)	(11%)	(14%)	(33%)

Panel B: Endogeneity tests, post-subprime (2007:Q2-2009:Q2)

	AAA	AA	A	BBB	spec
Amihud	-5.03^{***}	-1.06	-0.20	-0.60	-2.82^{***}
	(41%)	(31%)	(30%)	(27%)	(42%)
Roll	-5.24^{***}	-1.15	0.51	0.77	-2.89^{***}
	(33%)	(15%)	(21%)	(16%)	(23%)
firm zero	5.50^{***}	-1.12	-0.40	-0.82	-3.06^{***}
	(87%)	(35%)	(24%)	(44%)	(58%)
bond zero	6.40^{***}	1.10	-0.21	-0.70	-3.26^{***}
	(79%)	(73%)	(70%)	(68%)	(76%)
turnover	-6.17^{***}	-1.15	0.32	0.73	2.91^{***}
	(27%)	(16%)	(17%)	(20%)	(36%)
URC	-4.94^{***}	-0.84	-0.26	0.77	-2.72^{***}
	(50%)	(42%)	(49%)	(39%)	(63%)
Amihud risk	-5.07^{***}	-1.05	-0.36	-0.59	-2.69^{***}
	(21%)	(22%)	(34%)	(45%)	(50%)
URC risk	-4.82^{***}	-0.74	0.57	-0.75	-2.75^{***}
	(39%)	(34%)	(48%)	(34%)	(55%)

Table 9: Endogeneity tests. For each rating class R and each liquidity variable L we test for potential endogeneity bias by using a Durbin-Wu-Hausman test. In total 56 tests are run (8 liquidity variables $\times$ 5 rating classes) pre- and post-subprime. This table shows for each test the t-statistics and R^2 for the first stage regression in parenthesis. The proxies are described in detail in Section 4 and are calculated quarterly from $2004:Q4$ to $2009:Q2$. Panel A shows the coefficients using data before the subprime crisis, while Panel B shows the coefficients using data after the onset of the subprime crisis. Significance at 10% level is marked '*', at 5% marked '**', and at 1% marked '***'.

Panel A: Liquidity component in basis points, pre-subprime (2004Q4-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	1.6	1.1 (0.8;1.4)	1.7 (1.2;2.1)	2.0 (1.4;2.5)	162	178	193
AA	1.7	1.1 (0.8;1.5)	1.8 (1.3;2.3)	2.3 (1.6;3.0)	704	667	498
A	2.8	1.7 (0.9;2.6)	2.9 (1.5;4.3)	3.8 (1.9;5.5)	1540	1346	1260
BBB	4.0	2.9 (1.4;4.4)	4.1 (1.9;6.2)	4.9 (2.3;7.3)	517	270	553
spec	57.8	45.2 (33.9;57.4)	44.1 (33.1;56.0)	84.2 (63.2;106.9)	270	324	480

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2009:Q2)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	1.0	0.5 (0.3;5.4)	0.8 (0.5;8.1)	1.7 (0.9;16.6)	110	149	155
AA	40.6	22.9 (11.5;35.2)	36.1 (18.2;55.5)	63.0 (31.8;96.8)	493	572	483
A	47.6	25.0 (12.9;37.6)	47.9 (24.7;72.1)	70.0 (36.1;105.4)	762	878	890
BBB	94.0	65.2 (36.0;97.4)	117.2 (64.8;175.1)	99.5 (55.0;148.6)	123	159	256
spec	189.9	119.3 (79.4;154.9)	216.3 (144.0;280.9)	234.2 (156.0;304.2)	133	129	201

Table 10: Liquidity Component in basis points when the Treasury rate is used as riskfree rate. For each rating R we run the pooled regression

$$spread_{it}^{R} = \alpha^{R} + \beta^{R}\lambda_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i refers to bond, t to time, and λ_{it} is our liquidity measure. The bond spread is measured with respect to the Treasury yield. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we sort increasingly all values of λ_{it} and find the median value λ_{50} and the 5% value λ_5. The liquidity component in the bucket is defined as $\beta(\lambda_{50} - \lambda_5)$. This table shows for all buckets the liquidity component with standard errors in parenthesis. Confidence bands are found by a wild cluster bootstrap.

Panel A: Liquidity component in basis points, pre-subprime (2004Q4-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	1.4	1.0 (0.5;1.3)	1.2 (0.7;1.7)	2.0 (1.1;2.8)	162	178	193
AA	1.7	1.1 (0.4;1.7)	1.6 (0.6;2.6)	2.4 (0.9;3.8)	704	667	498
A	4.4	2.8 (1.2;4.3)	4.3 (1.8;6.8)	6.1 (2.6;9.6)	1540	1346	1260
BBB	8.4	5.8 (2.4;9.1)	8.9 (3.6;13.9)	10.4 (4.2;16.3)	517	270	553
spec	117.1	81.5 (61.2;104.4)	90.4 (67.9;115.8)	179.4 (134.6;229.6)	270	324	480

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2009:Q2)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	9.2	4.4 (0.9;7.9)	8.0 (1.7;14.2)	15.2 (3.2;27.3)	110	149	155
AA	68.5	37.8 (21.2;53.4)	64.0 (35.8;90.5)	103.9 (58.1;146.9)	493	572	483
A	92.6	53.8 (29.4;78.8)	95.9 (52.5;140.6)	128.1 (70.1;187.7)	762	878	890
BBB	176.5	138.6 (76.0;203.3)	201.6 (110.5;295.6)	189.4 (103.8;277.8)	123	159	256
spec	420.5	294.0 (196.2;383.0)	390.5 (260.6;508.7)	577.1 (385.2;751.8)	133	129	201

Table 11: Liquidity Component in basis points for an illiquid bond. For each rating R we run the pooled regression

$$spread_{it}^{R} = \alpha^{R} + \beta^{R}\lambda_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where i refers to bond, t to time, and λ_{it} is our liquidity measure. The bond spread is measured with respect to the swap rate. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we sort increasingly all values of λ_{it} and find the 75% value λ_{75} and the 5% value λ_5. The liquidity component in the bucket is defined as $\beta(\lambda_{75} - \lambda_5)$. This table shows for all buckets the liquidity component with standard errors in parenthesis. Confidence bands are found by a wild cluster bootstrap.

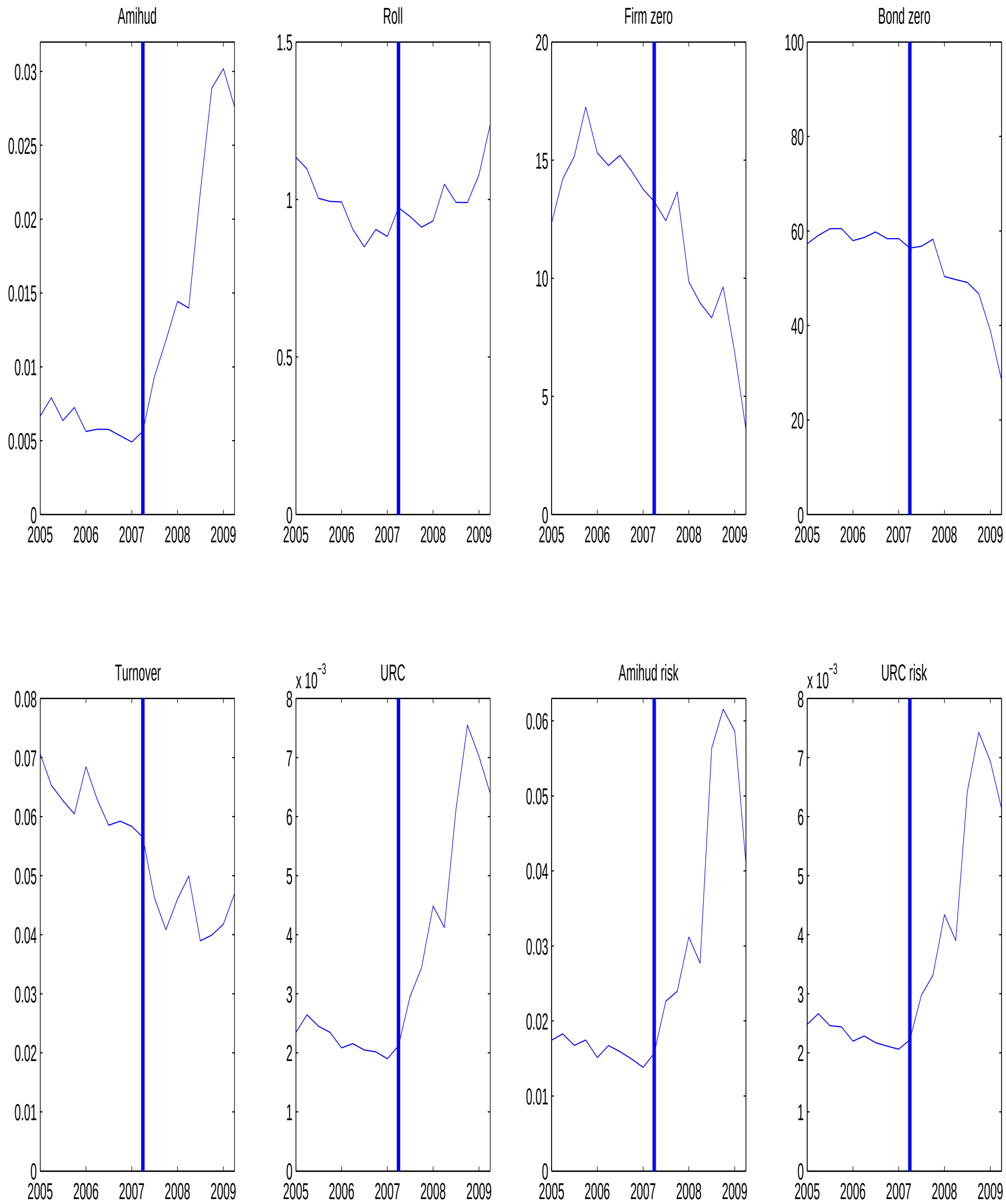

Figure 1: Time series of liquidity variables in the regression sample. This graph plots the time series of liquidity variables along with a line marking the start of the subprime crisis (beginning in 2007Q2). Liquidity variables are measured quarterly, and for every liquidity variable the mean value of the variable across all observations each quarter is graphed. For each quarter a bond observation requires a full set of accounting variables and at least four transactions during the quarter.

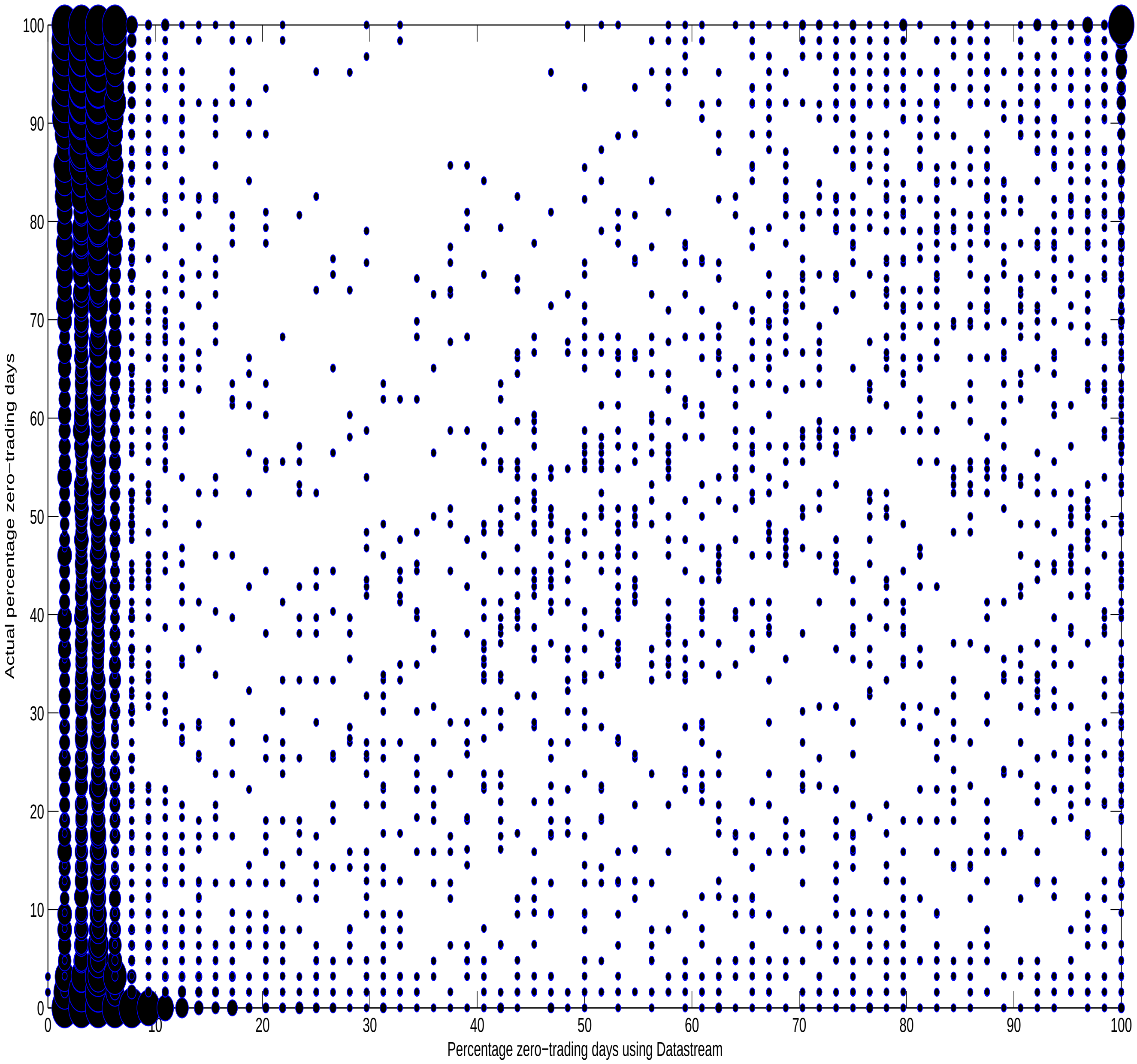

Figure 2: Zero-trading days using Datastream. This graph plots for every bond in the sample and every quarter from 2005:Q1 to 2007:Q4 the percentage zero-trading days using Datastream on the x-axis and actual percentage zero-trading days (based on all trades in TRACE) on the y-axis. The thickness of a point depends on the number of observations in that point. The total number of observations is 60,680.

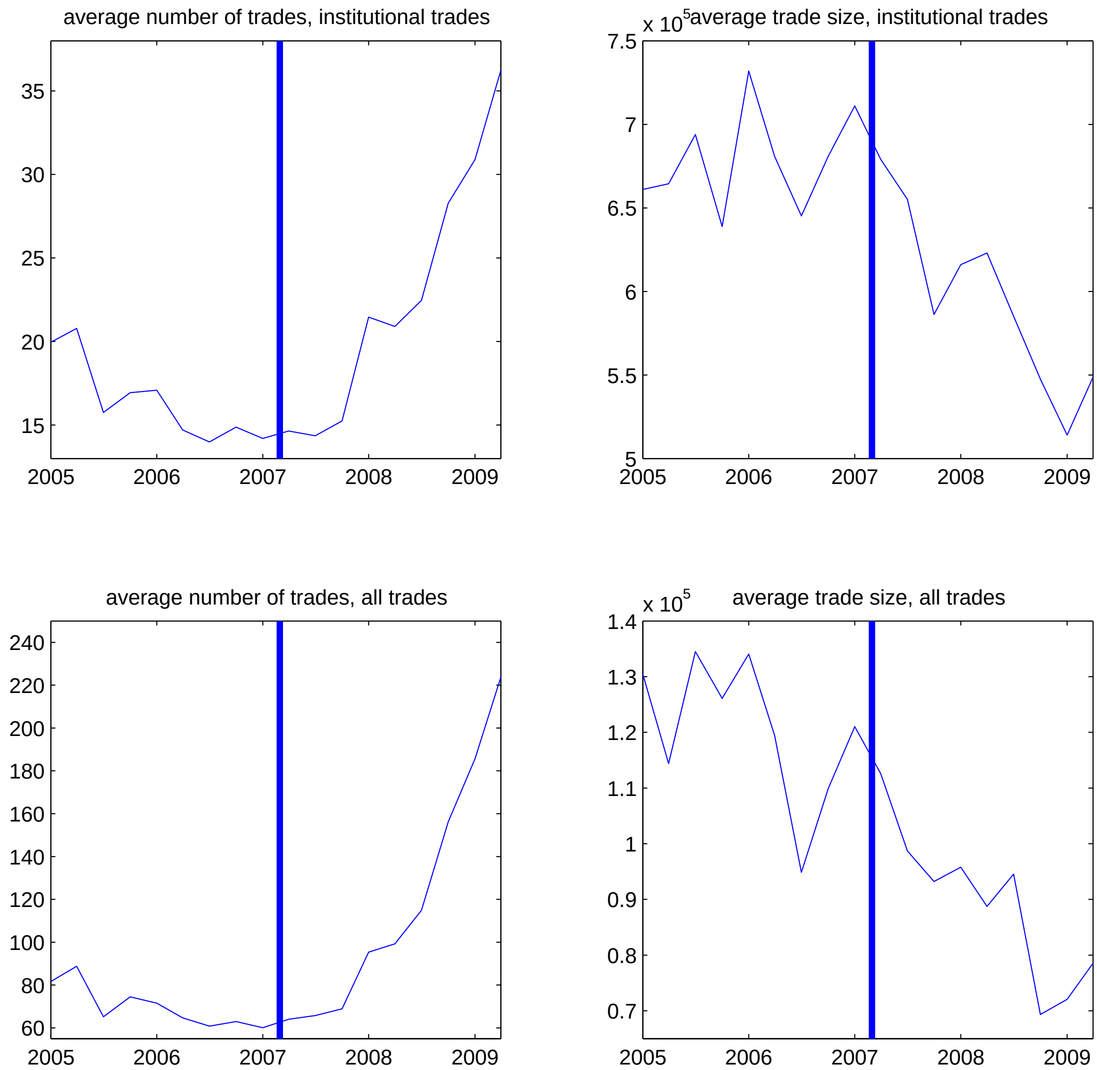

Figure 3: Time series of average number of trades and average trade size in the full sample. This graph plots the time series of average number of trades in a quarter and average trade size along with a line marking the start of the subprime crisis (beginning in 2007.Q2). Number of trades and trade size are measured quarterly and the mean value across all observations each quarter is graphed. A bond is included in every quarter if it traded at least one time during the sample period 2005:Q1-2008:Q4. The top graphs is based on institutional trades, i.e. trades of size $\$100,000$ or more, while the bottom graphs are based on all trades.

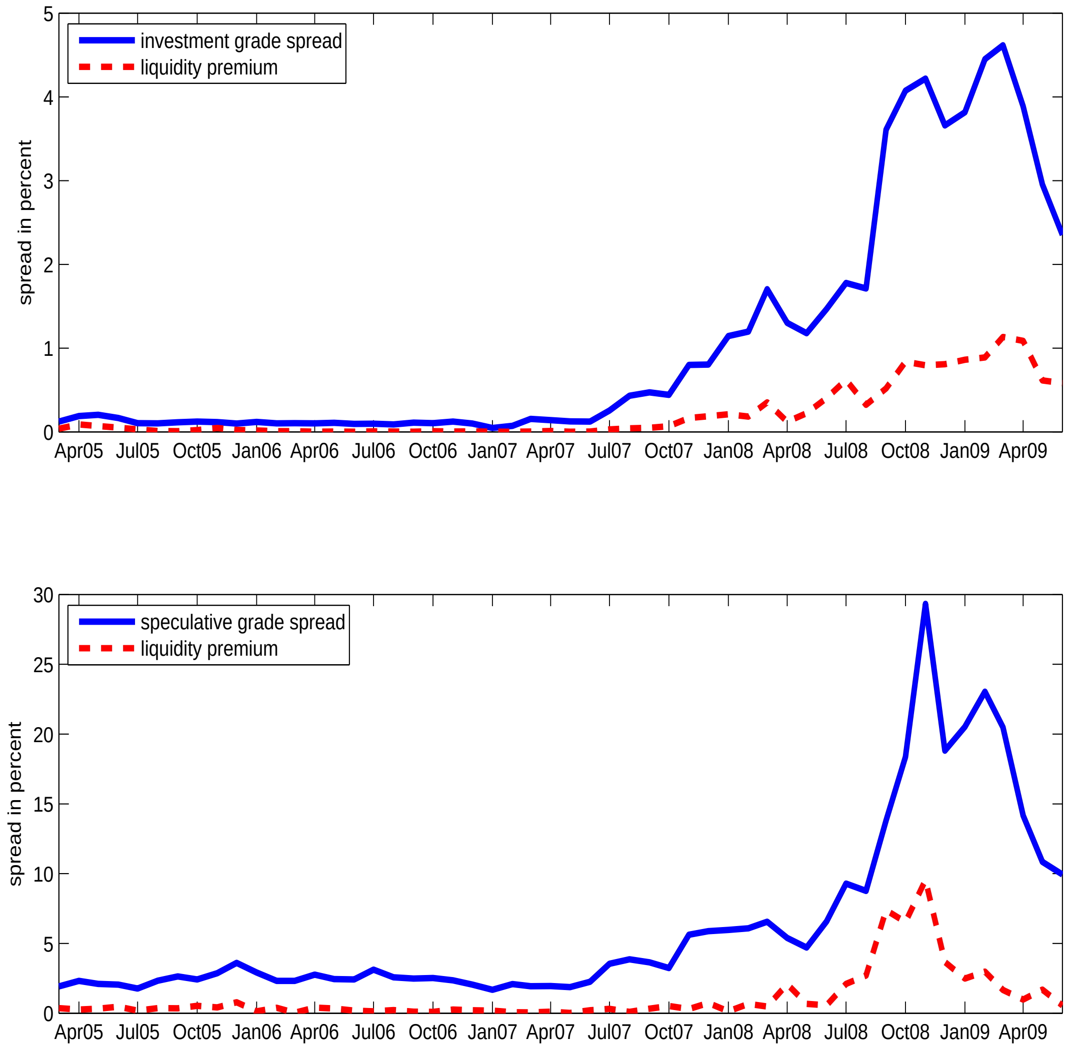

Figure 4: Liquidity premium and total spread for investment grade and speculative grade bonds. This graph shows for investment grade and speculative grade yield spreads the variation over time in the amount of the spread that is due to illiquidity and the total yield spread. On a monthly basis, the fraction of the yield spread that is due to illiquidity is calculated as explained in Section 5.4. This fraction multiplied by the median yield spread is the amount of the spread due to illiquidity and plotted along with the median yield spread.

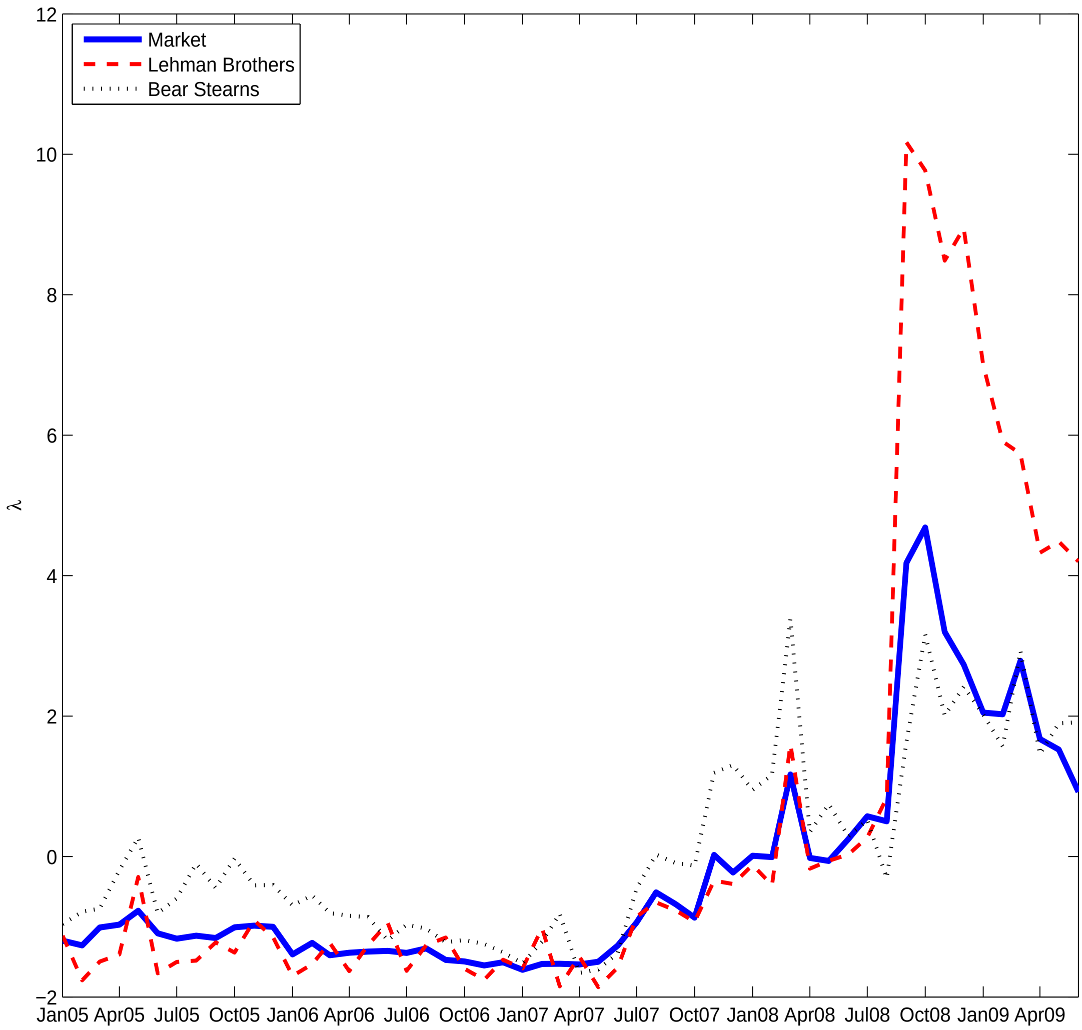

Figure 5: Illiquidity of bonds underwritten by Lehman Brothers and Bear Stearns. This graph shows the time series variation in illiquidity of bonds with Lehman Brothers as lead underwriter, bonds with Bear Stearns as lead underwriter, and all bonds in the sample. For every bond underwritten by Lehman Brothers their (il)liquidity measure λ is calculated each month and a monthly weighted average is calculated using amount outstanding for each bond as weight. The graph shows the time series of monthly averages. Likewise, a time series of monthly averages is calculated for bonds with Bear Stearns as a lead underwriter and all bonds in the sample. Higher values on the y-axis imply more illiquid bonds.

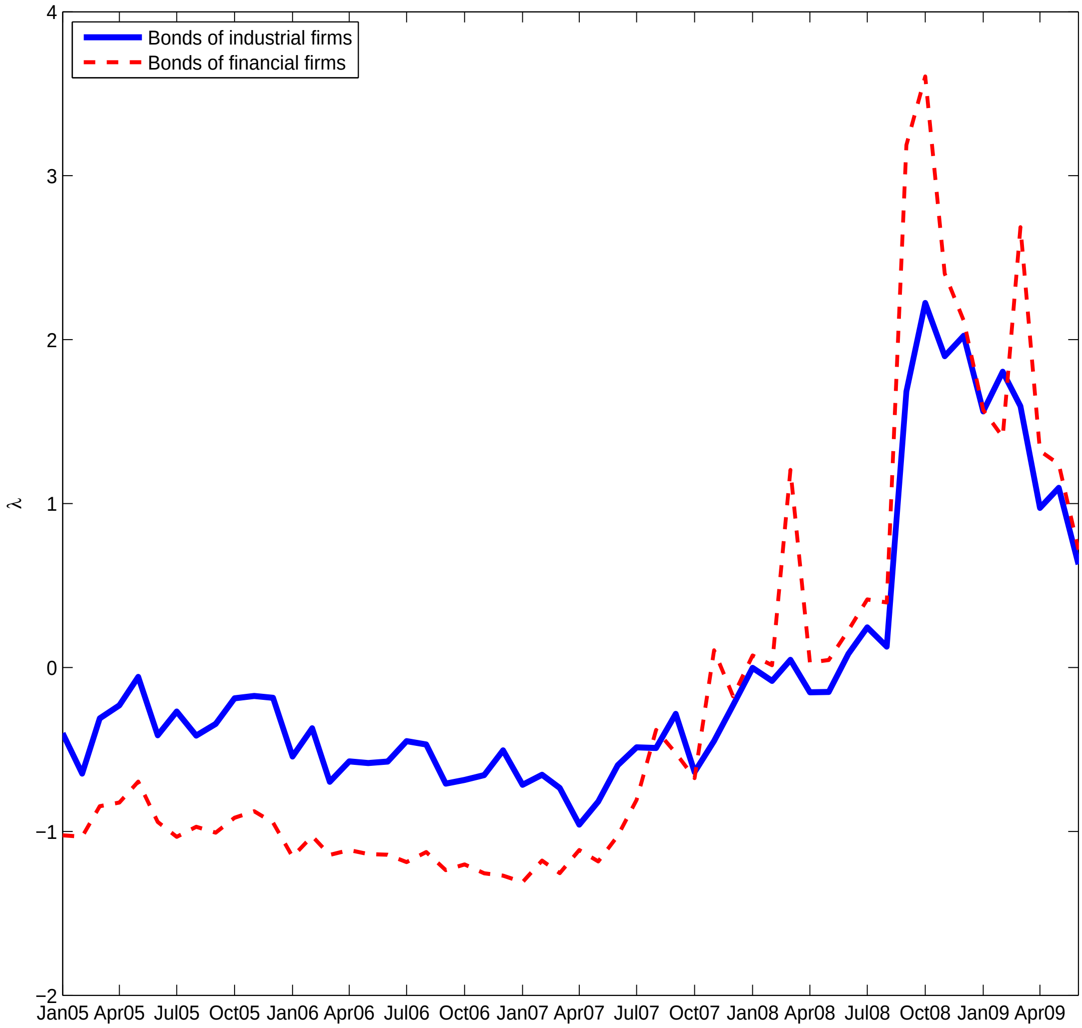

Figure 6: Illiquidity of bonds of industrial and financial firms. This graph shows the time series variation in illiquidity of bonds of industrial and financial firms. For every bond issued by a financial firm their (il)liquidity measure λ is calculated each month and a monthly weighted average is calculated using amount outstanding for each bond as weight. The graph shows the time series of monthly averages. Likewise, a time series of monthly averages is calculated for bonds issued by industrial firms. Higher values on the y-axis imply more illiquid bonds.