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 available through TRACE with the unique natural experiment provided by the onset of the sub-prime crisis. We find that before the onset of the crisis, liquidity premia for the most liquid segment of investment grade bonds were small but they increased dramatically at the onset of the crisis. Among the liquidity proxies examined, the Amihud price-impact measure and a measure of transaction costs are the strongest drivers of liquidity both across rating and time. In contrast to earlier studies we find no positive relationship between the number of days a bond does not trade and the yield spread.

Keywords: Corporate bonds; Yield spreads; Liquidity; Subprime crisis; TRACE

JEL: G10; G12

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1 Introduction

Corporate bonds are widely regarded as illiquid securities, and their illiquidity 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.

There is convincing evidence that at least part of this non-default component can be attributed to illiquidity of corporate bonds. For example, Longstaff et al. (2005) argue that the pure credit component of a corporate bond spread can be measured through the premium on a credit default swap referencing the bond. By essentially subtracting the CDS premium from the corporate bond spread, they obtain a 'non-default component' and show that this component is correlated with proxies for liquidity both in the cross section and in the time series. Furthermore, Chen et al. (2007) regress corporate bond spreads on proxies for liquidity and credit risk and find that coefficients on several liquidity proxies are significant. Both papers contain important information on the sensitivities of spreads to changes in liquidity proxies, but they do not give us estimates of the size of the liquidity component.

In this paper we assess the magnitude of the liquidity component of individual bonds. We do this by regressing corporate bond spreads on proxies for liquidity while controlling for credit risk and estimate a 'liquidity score' of a given bond by multiplying the liquidity regression coefficients with the corresponding regressors. This allows us (within a given rating class and maturity) to obtain a distribution of liquidity scores and define the liquidity component of an average bond as the difference between the median and the 5% quantile in this distribution. Our regression analysis is based on actual transactions data obtained from TRACE (see below) through a period covering the onset of the subprime crisis. Our regressions in combination with the source of data and the period we cover provide new insights into the liquidity of corporate bonds.

The regression analysis relies on various measures of trading frictions that proxy for liquidity effects. For such measures it is critical that our data source is not contaminated by prices which do not represent actual trades. The importance of this shows up, for example, when considering the measure 'zero trading days' of a bond, i.e. the proportion of days within the observation period in which there is trade in the bond. This measure is used in Chen et al. (2007) but their measure is based on Datastream. These data are, as we will see, contaminated by matrix pricing or other price adjustments which are not based on actual transactions. When the zero trading day measure based on TRACE is used, we find that this measure does not proxy for liquidity. A consequence of revising the zero-trading measure is that the LOT measure employed in Chen et al. (2007) becomes unrealistically large and therefore hard to use.

There are additional insights to be gained from using transactions data. Large trades can be separated from small trades and therefore we can restrict our attention to the pricing of bonds among better informed, large (probably institutional) traders. The differences in pricing and transactions costs facing these two types of investors has been documented in several studies Edwards et al. (2007), Goldstein et al. (2007), and Bessembinder et al. (2006) but how liquidity measures are affected has not been examined. For example, the Amihud measure, which measures the price impact of trades, is greatly reduced. Using large trades only, the median price impact of a 300.000 dollar trade is roughly 0.1%, whereas Han and Zhou (2007) using all trades obtain an impact of 10.2%.

Contrary to Edwards et al. (2007), Goldstein et al. (2007), and Bessembinder et al. (2006) we do not have access to information on whether trades were executed at the bid or the ask or what type of agent executed the trade. However the trading volume information allows us to construct a transaction cost measure measure, unique roundtrip costs (URC). This measure is based on prices at which we can reasonably assume that the same lot of bonds has been traded at both sides of the bid-ask within a very short period of time. In our regressions, we find that this measure has stronger explanatory power than the popular Roll measure.

In addition to URC, market depth as measured through the Amihud measure is a key explanatory variable. In fact, these two variables are the key channels through which the liquidity component increases at the onset of the subprime crisis. In particular, the increase in liquidity spreads takes place not only through the increase in the Amihud measure but also through a higher sensitivity to this measure.

The subprime crisis has drastically increased the size of the liquidity spread. For example, before the onset of the crisis, the average (across maturities) A-spread was 6.2 bps, whereas after the onset it increased to 41.9 bps. Throughout the sample, the liquidity premium is increasing with time-to-maturity. Before the subprime crisis the premium for 0-2 yr A bonds was

3.8 bps and 9.4 bps for the 5-30 yr segment. After the onset of the crisis these numbers increased to 30.3 bps and 57.1 bps, respectively.

The structure of the paper is as follows: In Section 2 we review the literature on corporate bond liquidity and touch briefly also on the recent literature on liquidity of CDS contracts. While illiquidity of corporate bonds clearly influences their pricing, we also list reasons why the effect may not be very large. This discussion motivates the inclusion of several explanatory variables in our regressions. Section 3 describes the data set we are using. Section 4 explains the regressions we are running focusing on the choice of variables controlling for credit risk and variables proxying for liquidity. In Chapter 5 we start by giving some of the most important summary statistics. We then explains our results both for the univariate regression (in which we control for credit risk but include only one liquidity proxy) and then for the multivariate regressions in which all liquidity proxies are simultaneously included. We conduct regressions separately for the period before and after the onset of the subprime crisis, and discuss the overall effect on liquidity of this event and the channels through which this increase in the liquidity component takes place. Section 6 conducts robustness checks and Section 7 concludes.

2 Literature review - INCOMPLETE

The liquidity of a financial asset is meant to capture the ease by which it is traded. An asset which is not perfectly liquid violates the frictionsless trading assumptions underlying no-arbitrage and standard equilibrium models of pricing. Early empirical studies on liquidity have focused on equity markets and on government bond markets since good data have been available for a number of years in these markets. A comprehensive survey of both the different notions and the empirical evidence of liquidity can be found in Amihud, Mendelson and Pedersen, and we will not survey the general contributions on liquidity in this paper. We will focus instead on the more recent wave of papers which specifically address liquidity in corporate bond markets and in the closely related markets for credit default swaps (CDS contracts).

There are many reasons why illiquidity is expected to have an impact on corporate bond prices. Prior to the TRACE initiative, corporate bond markets were very non-transparent. Trade prices were essentially only known by a limited set of dealers. When bid-ask prices were known, spreads tended to be large and trading frequency low. The first research papers using TRACE transactions data show that the enhanced price transparency following the dissemination of prices has lowered transaction costs for investors, see Edwards et al. (2007), Goldstein et al. (2007), and Bessembinder et al. (2006). This would suggest that liquidity has increased However, as shown in Goldstein et al. (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. In addition, credit risky instruments tend to become illiquid during financial crises, and this could also have an impact on the price and therefore on the spreads, see Acharya and Pedersen (2005).

There are, however, also a number of reasons why we might not expect liquidity spreads to be very large - at least if properly measured. First, TRACE allows us to separate large trades from small trades, and thus to focus on institutional trades. Before TRACE, this distinction was not possible. We will show that this distinction is critical for several measures of liquidity. Second, search based explanations for liquidity effects, see for example Duffie et al. (2005), incorporate the discounted value of all future search costs in connection with sale of the asset. That is, not only is the current price of an asset affected by the search costs in connection with getting rid of the asset at a later date - the sale price is affected by the buyer's anticipated costs in getting rid of the asset at a future date etc. But a corporate bond matures, meaning that a the maturity date, if there is no default, the bond is converted into the most perfectly liquid asset of all, namely cash. Third, perhaps because of the automatic conversion to cash, corporate bonds are popular instruments for large buy-and-hold investors. While this of course contributes to the relative infrequent trading of bonds, it may not be the case that the recorded transactions prices have a large liquidity component, simply because the buy-and hold investors do not anticipate any costs of future trading. Fourth, even if the corporate bond depends on the default risk of a firm, it has a simple pay-off structure as long as the issuer avoids default. This means that uncertainty in the favorable scenarios of the issuer's performance is not critical for the determination of the corporate bond price.

For evidence in support of this puzzle, se for example Huang and Huang (2003) who calibrate structural default risk models in such a way that the default probabilities and recoveries of corporate bonds are matched in the model. They then 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.

3 Data description

Corporate bond transactions data only recently became available on a large scale. Since January 2001 FINRA[1] members 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. The dissemination has taken place in three steps:

1. July 1, 2002. Dissemination of trades in investment grade issues with initial issuance of at least $1 billion and dissemination of trades in the 50 high yield bonds which formerly were contained in FIPS.

2. March 3, 2003. Dissemination of trades in bonds with initial issuance of at least $100 millions and with a rating of at least A3/A-. On April 14 same year dissemination of trades in 120 BBB bonds.

3. October 1, 2004. Final phase of the dissemination. All trades are disseminated from here on.

As of July 1, 2005, all trades must be reported within 15 minutes [2]. TRACE covers all trades in the secondary over-the-counter market for corporate bonds and accounts for more than 99% of the total secondary trading volume in corporate bonds. The only trades not covered by TRACE are trades on NYSE which are mainly small retail trades.

We use a sample of straight coupon bullet bonds with trade reports from October 1, 2004 to March 31, 2008. This provides us initially with 7,506 bond issues. Standard and Poor's rating at all dates in the sample period is downloaded from Datastream and bonds with missing rating are excluded. The final sample contains 4,281 bonds. For these bonds we collect the trading

[1] The Financial Industry Regulatory Authority formerly named National Association of Security Dealers (NASD).

[2] This requirement has gradually been tightened from 1 hour and 15 minutes to 15 minutes. In practice 80% of all transactions are reported within 5 minutes.

history from TRACE covering the period from October 1, 2004 to March 31, 2008 and after filtering out erroneous trades we are left with 6,329,107 trades[3]. Finally we collect share prices for the issuing firms from CRSP, firm accounting figures from Bloomberg, swap rates from Datastream, and LIBOR rates from British Bankers' Association.

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. Retail sized trades (trade below $100,000 in volume) are disregarded and observations where a bond did not trade in the last month of the quarter are excluded. Yield spreads are calculated as the difference between the year-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 did not have the opportunity to trade for the entire quarter or had less than one month to maturity.

To control for credit risk, we follow Blume et al. (1998) and others and add ratio of operating income to sales, ratio of long term debt to assets, leverage ratio, equity volatility and 4 pretax interest coverage dummies to the regressions. 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. Finally we add bond age, time-to-maturity, and size of coupon to the regressions. Later in the paper we show that results concerning the size of a liquidity component in corporate bond spreads are robust to whether we define bond age and size of coupon as liquidity or credit risk proxies.

[3]Any trade report entered in TRACE are kept, so a number of trade reports contain errors which are corrected in TRACE by subsequent correction trade reports. See Dick-Nielsen (2009) for more on this.

For each rating class we run separate regressions using quarterly observations. The regressions are

$$
\begin{aligned}
\text{Spread}_{it} = \alpha + \gamma \text{ Liquidity}_{it} + \beta_1 \text{ Bond Age}_{it} + \beta_2 \text{Amount Issued}_{it} \\
+ \beta_3 \text{ Coupon}_{it} + \beta_4 \text{Time-to-Maturity}_{it} + \beta_5 \text{ Eq.Vol}_{it} + \beta_6 \text{ Operating}_{it} \\
+ \beta_7 \text{ Leverage} + \beta_8 \text{ Long Debt}_{it} + \beta_{9,pretax} \text{ Pretax dummies}_{it} + \epsilon_{it}
\end{aligned}
\tag{1}
$$

where i is bond issue, t is quarter, and Liquidity_{it} contains one or several liquidity proxies defined below. If we run a regression with one liquidity variable γ and Liquidity_{it} are numbers, while they are vectors if we run a regression with all liquidity variables. 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 (2008)). This corrects for time series effects, firm fixed effects and any heteroscedasticity in the residuals.

Next we define the liquidity proxies. We winsorize the 0.5% highest values of every liquidity variable.

4.2 Liquidity Measures

Liquidity of an asset can be described as the ease with which the asset can be traded. Since there is no single measure that adequately describes the liquidity of an asset, we define several liquidity measures for corporate bonds in this section. In doing so, we hope to capture the different aspects of corporate bond liquidity.

4.2.1 Amihud measure (price impact of trades)

If an asset is very liquid one can trade large quantities of the asset without moving the price, so price movements must to some degree reflect the market depth for the asset. Amihud (2002) constructs an illiquidity measure that is based on the theoretical model of Kyle (1985), 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 $N_t - 1$ is the number of trades on day t. At least two transactions is required on a given day in order to calculated 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 are bid-ask spreads, but they are not directly observable in the corporate bond market. Roll (1984) find that under certain assumptions the effective bid-ask spread equals two times the squareroot of minus the correlation 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.

4.2.3 Unique roundtrip cost (bid-ask spread)

An alternative measure of bid-ask spreads is proposed in Feldhütter (2008) and is based on *unique roundtrip trades* (URT). For a given bond on a given day, if there are exactly 2 or 3 trades for a given volume, they are part of a URT. The intuition is that either 1) a customer sells a bond to a dealer who sells it to another costumer, or 2) a customer sells a bond to a dealer, who sells it to another dealer, who ultimately sells it to a costumer. Since there is no information in TRACE about who is on the sell or buy side, this procedure provides an estimate of this. For a URT we define the unique roundtrip cost (URC) as

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

where P_{max} is the maximal price in the URT and P_{min} is the minimal 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.

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 to the year. We can interpret the inverse of the turnover as the average holding time of the bond, i.e. a turnover of 0.5 implies an average holding time of about 6 month.

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.

Illiquidity of a bond reflects to some extend uncertainty about the fundamental value of the bond. The uncertainty about the fundamental value of a bond is reduced if the issuing firm has issued other bonds that trade frequently, since we can extract information about the firm from the frequently traded bonds. Thus, we also calculate *firm zero-trading days* as the percentage of days during a quarter where none of the issuing firm's bonds traded. Firm zero-trading days for different bonds issued by the same firm is therefore the same.

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

The main drivers of liquidity risk in our regressions are the Amihud measure and unique roundtrip costs. Following Acharya and Pedersen (2005) it is likely that investors also consider the covariation of these measures with market returns and with market-wide illiquidity and that therefore the variability of these measures play a role for liquidity spreads. Acharya and Pedersen document that the most important contribution to return from illiquidity comes from the covariance between the asset specific illiquidity and market returns - i.e. investors require extra compensation for holding assets which are illiquid when asset returns are low. This suggests adding a beta to our regressions measuring covariation between illiquidity costs and market returns. Since this beta is linear in the standard deviation of illiquidity costs and we assume that illiquidity costs are linear in our liquidity measures, we include in our regressions the quarterly standard deviations of the daily Amihud measure and unique roundtrip costs.

5 Results

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 the average bond in the sample 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 71.4% 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 1.6%. 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 0.0034 implying that a trade of $\$300,000$ in an average bond moves price by roughly 0.10%. Han and Zhou (2007) also calculate the Amihud measure for corporate bond data using TRACE data, but 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 0.18% according to the URC measure, while the roundtrip cost is less than 0.033% for the 5% most liquid bonds. Thus, transaction costs are modest for a large part of the corporate bond market. The roundtrip cost measured using URC is significantly lower than the median roundtrip cost of 0.48% when estimated using the Roll measure. Not only is the Roll bid/ask spread higher than URCs for the median bond, but for all other quantiles as well. There are two possible explanations for this surprising difference between the Roll and URC bid/ask spread. Bao et al. (2008) argue that the Roll measure captures the price impact of a transitory illiquidity component above and beyond the effect of simple bid-ask bounce. Alternatively, the difference might be explained by the statistical properties of the Roll measure. Harris (1990) finds that "(t)he serial covariance estimator is very noisy in daily data and is biased downward in small samples. The Jensen's inequality bias in Roll's spread estimator is very serious in daily and weekly data."[5]

The correlations of the liquidity measures in Panel B of Table 1 reveal several interesting aspects of liquidity and liquidity risk. The correlation of 83% between URC and URC risk and 59% 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 high correlation between liquidity and liquidity risk. We are also warned that signs of especially URC and URC risk in later regressions where they both enter should be interpreted with caution due to collinearity problems. Interestingly, there is a high correlation of 66% between market depth (Amihud) and bid/ask spread (URC).

Liquidity is a rich concept that has many facets and cannot be proxied by a single measure. By including a number of variables in our analysis that proxies for important characteristics of liquidity we are confident that main aspects of liquidy are captured.

[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 (2007) 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.

[5] A third explanation is that URCs are downward biased estimates of bid-ask spreads. However, Feldhütter (2008) finds that the URC estimates for the sample period in Edwards et al. (2007) (January 2003-January 2005) match the estimates in EKP well suggesting that URC estimates are reliable.

5.2 Marginal effect of liquidity proxies

We have defined eight liquidity proxies and in this section we ask if the proxies are priced. For each variable we run the pooled regression in Equation (1), and run separate regressions for a) each of the seven rating categories and b) before and after the subprime crisis. We windsorize the 0.5% highest and lowest spreads and the 5% highest Roll measures to make the results robust to outliers. Running separate regressions for different rating categories shows us if the variables affect bonds of various credit quality different 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, since the pre-subprime period was a period with plenty of liquidity while the market in the post-subprime period has suffered from a strong lack of liquidity. Table 2 shows the regression coefficients for each of the variables.[6]

For the pre-subprime period both proxies for the bid-ask spread, Roll and URC, have positive coefficents for all rating categories. All 7 coefficients are significant for URC while 5 out of 7 are significant for the Roll measure. Also, it is evident that bid/ask spreads are important for spreads post subprime. The statistical power is lower for this period since the number of observations are fewer, but there is a positive sign for 5 out of 7 coefficients for Roll and again all coefficients are positive for URC. In addition, 4 coefficients are significant URC while 2 are for Roll. Transaction costs are clearly priced consistent with the results in Chen et al. (2007) who find that bid/ask spreads are priced, and the statistical results are stronger for URC than for Roll.

We see that Amihud is strongly significant before subprime with all coefficents positive. After subprime the Amihud coefficients remain positive and although only two of the coefficients are significant due to the lack of statistical power, they are for investment grade ratings much larger in magnitude. In addition to the increase in the market price pr unit lack of market depth, the top-left graph in Figure 2 shows that the lack of market depth has increased strongly during the subprime crisis. Thus, an important determi-

[6]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 proxy 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.

nant for corporate bond spreads post subprime is the ability to sell without moving the price too much.

Turning to zero trading days Table 2 shows surprisingly that spreads depend *negatively* on the number of zero trading days. For bond and firm zeros 23 out of 28 coefficients are negative, and half of them significantly negative. Constantinides (1986) finds theoretically that in the presence of transaction costs, investors will trade infrequently, and consistent with this line of reasoning Chen et al. (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 et al. (2007) is likely to be the data source. While we use actual transaction data and can directly detect when a trade occurs, Chen et al. (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 1 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. While zero-trading days are not correctly identified in Datastream, the LOT measure of Chen et al. (2007) could be a relevant measure to include in our analyse. Therefore we have calculated a yearly LOT measure as in Chen et al. (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 we consider too high compared to the other measures of roundtrip costs in this paper.

From a theoretical point of view the negative 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.[7]

[7] Goldstein et al. (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

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, namely the variance of liquidity. A priori, volume might affect spreads in both directions. For the pre-subprime period volume is significantly negative for five out of seven coefficients, so the dominant role of volume in this period is to proxy for liquidity. We see that liquidity risk is priced since Amihud and URC risk are both significantly positive in five out of seven rating categories. For the post-subprime period turnover coefficients are positive for speculative grade and mainly positive for investment grade, often with significant coefficients. This suggests that turnover's role as a proxy for liquidity risk is strongest for the more credit risky bonds. The importance of liquidity risk for speculative grade bonds is reinforced by the significantly positive Amihud and URC risk coefficients. URC risk has positive coefficients for all rating categories post subprime, many of them significant. Overall, there is clear evidence that liquidity risk in corporate bonds is priced, but volume is not a good proxy for this risk.

5.3 Size of liquidity component

Table 3 shows the regression coefficients from the regression

$$Spread_{it} = \alpha + \gamma Liquidity_{it} + \beta Credit\ risk_{it} + \eta Pretax\ dummies + \epsilon_{it}$$

where $Liquidity_{it}$ is a vector of values of the seven liquidity proxies, $Credit\ risk_{it}$ is a vector of values of credit risk controls, i denotes the bond, and t is the quarter. The regression is carried out for each rating category and for both the pre- and post subprime period. We exclude firm zero as a liquidity variable because there are some collinearity issues in AA post subprime.

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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.

To calculate the impact of corporate bond liquidity on yield spreads we do the following. For each bond-quarter observation we define the liquidity score as $\gamma Liquidity_{it}$. Within a given rating (AAA, AA, A, BBB, BB, B, C), 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 4 shows the size of the liquidity component. We see that the liquidity component depends on rating and 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 2.2bp for AAA, 2.2bp for AA, 7.1bp for A, and 13.8bp for BBB. The size of the component is similar in magnitude to the nondefault component in corporate bond spreads found by subtracting the CDS premium from the corporate - swap spread (swap basis).[8] For speculative grade the liquidity component is much larger and estimated to be 68.4bp for BB, 147.7bp for B, and 410.5bp for CCC. 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]

There is a dramatic increase in the liquidity component in the post-subprime period for all but the two worst rating categories as Panel B in Table 4 shows. The component increases by a factor 2-10 in the investment grade bonds while the evidence is more mixed for the speculative grade bonds (likely due to a small sample). This underscores that liquidity has dried out under the subprime crisis and part of the spread widening for bonds is due to a higher liquidity premium. We are able to draw this conclusion because we look at different aspects of liquidity through a number of liquidity prox-

[8] Longstaff et al. (2005) find an average nondefault component of -7.2bp for AAA/AA, 10.5bp for A, and 9.7bp for BBB, Han and Zhou (2007) 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 et al. (2005) find it to be 6.9bp for AAA/AA, 0.5bp for A, and 14.9bp for BBB.

[9] Longstaff et al. (2005) report an average of 17.6bp for BB, while Han and Zhou (2007) estimate it to be 2.8bp for BB, -53.5bp for B, and -75.4bp for CCC.

ies. As Figure 2 shows some of the proxies indicate that liquidity conditions changes strongly after the crisis, namely Amihud and URC, while turnover, firm zero-trading days, and Roll do not show much reaction to the onset of the crisis.

Turning to the term structure of liquidity, we see that the liquidity component increases as maturity becomes higher in the pre-subprime period although the differences are modest in absolute terms since the components are generally small. However, the post-subprime period provides us with a clear lens through which the term structure effects of liquidity can be studied since the liquidity components are much larger. We see that the increasing term structure of liquidity is robust to the choice of sample period; for most rating classes liquidity is increasing as a function of maturity. This seemingly contrasts the work of Ericsson and Renault (2006) who find a downward sloping term structure of liquidity. However, they use two dataset, one is transaction data from NAIC and the other is Datastream data, and only 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 (defined as the median corporate bond spread to the swap rate). 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 et al. (2004) and Feldhütter and Lando (2008)). Table 5 shows the fraction of the liquidity component to the total corporate-swap spread. The negative fractions for AAA and AA for the shortest maturity are not errors but merely reflect that swap rates in this period have a credit risk component of around 5-10 basis points according to estimates in Feldhütter and Lando (2008) leading to a negative corporate spread for highly rated issuers. For the pre-subprime period the liquidity fraction of the spread is generally decreasing with maturity and small at long maturities: except for B and CCC rated bonds the fraction is around 20% for long maturities while for shorter maturities it is roughly half the spread. For the post-subprime period the fractions are larger, so liquidity has not only increased strongly in absolute size but also increased in importance relative to credit risk. For long maturities the liquidity fraction of the spread is in the range $40-50\%$ on average while it is closer to $60-100\%$ for short maturities.

6 Robustness checks

In this section we show that the results are robust to the choice of benchmark riskfree rate, choice of liquidity variables, and the definition of the liquidity component.

6.1 Benchmark riskfree rate

The size of the nondefault component in corporate bond spreads investigated by among others Huang and Huang (2003) and Longstaff et al. (2005) depend strongly on the chosen riskfree rate. In Longstaff et al. (2005) the difference is around 60 basis points. As Table 6 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 for all but the most imprecisely junk bond components less than 10 basis points.

6.2 Liquidity proxies

In our analysis we have used seven *direct* measures of liquidity (based on actual transaction data), in contrast to most previous literature that use *indirect* measures, i.e. measures based on bond characteristics and/or end-of-day prices. See Houweling et al. (2005) for an extensive review of indirect measures of liquidity. In the analysis we have only used direct measures of liquidity because they are time-varying and more acurately reflect liquidity, and to the extent that indirect measures have explanatory power after including direct measures, they are likely to proxy for credit risk. However, since amount issued and age have often been used as indirect measures of liquidity, we check the robustness of our results be including those two variables in the estimation of the liquidity component. Table 7 shows the size of the liquidity component when age and amount issued are regarded as liquidity proxies. We see that there are some differences for the most risky rating categories and post-subprime the component is 10-15 basis points higher for short maturities in the investment grade segment, but the main conclusions in the paper are unchanged.

6.3 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 8 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. The Table shows that the obvious result that the liquidity component is larger for an illiquid bond compared to an average bond. Also, the Table shows that the main results of the paper are unchanged: the term structure of liquidity is increasing, the liquidity premium is much higher post subprime compared to pre subprime, and the liquidity premium for investment grade bonds are modest.

7 Conclusion

We have analyzed the extent to which yield spreads on corporate bonds can be attributed to bond illiquidity by regressing yield spreads on numerous proxies for illiquidity while controlling for credit risk. Our analysis is based on transactions data from TRACE data and the sample covers both the period before and after the onset of the subprime crisis. We find that before the onset of the subprime crisis, liquidity premia for the most liquid segment of investment grade bonds were very small but they increased at the onset of the subprime crisis. Before and after the onset, the strongest influence on yields comes from the Amihud measure, which measures the price impact of trades, and a measure of transactions costs which we denote unique roundtrip costs. These measures are important both through their levels and through their variability. We find limited significance of other popular measures, such as the Roll measure, which is a measure of transactions costs, and and zero trading days, which measures the fraction of days in which the bond does not trade. Consistent with the early studies on TRACE data, we find that distinguishing large trades from small trades critically influences measures of liquidity.

Panel A: Summary statistics for liquidity proxies

	Amihud	Roll	firm zero	bond zero	turnover	URC	Amihud risk	URC risk
99th	0.0981	8.12	95.3	98.4	0.308	0.0139	0.1018	0.01280
95th	0.0406	3.14	84.1	98.4	0.147	0.0081	0.0572	0.00760
75th	0.0092	0.94	20.6	88.5	0.072	0.0033	0.0230	0.00342
50th	0.0034	0.48	1.6	71.4	0.045	0.0018	0.0117	0.00181
25th	0.0011	0.27	0.0	40.6	0.026	0.0010	0.0049	0.00089
5th	0.0002	0.11	0.0	8.1	0.008	0.0003	0.0007	0.00021
1st	0.0000	0.06	0.0	1.6	0.002	0.0001	0.0001	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	0.30	1.00						
firm zero	−0.03	0.19	1.00					
bond zero	0.13	0.32	0.44	1.00				
turnover	−0.05	0.04	0.00	0.00	1.00			
URC	0.71	0.30	0.01	0.09	−0.01	1.00		
Amihud risk	0.59	0.21	−0.10	−0.12	−0.01	0.66	1.00	
URC risk	0.47	0.20	−0.09	−0.15	−0.02	0.83	0.67	1.00

Table 1: Statistics for liquidity and liquidity risk proxies. This table shows statistics for corporate bond liquidity and liquidity risk proxies. The proxies are described in detail in Section 4 and are calculated quarterly from 2005:Q1 to 2008:Q1. Panel A shows different quantiles for the proxies. Panel B shows the correlations among the proxies.

Panel A: Marginal liquidity regressions, pre-subprime (2005:Q1-2007:Q1)

	AAA	AA	A	BBB	BB	B	CCC
Amihud	1.04***	1.60***	1.31**	2.81***	14.42***	35.07***	3.02
	(6.54)	(7.62)	(2.20)	(2.69)	(2.59)	(3.67)	(0.37)
Roll	0.01***	0.05***	0.06***	0.02	0.09**	0.25*	0.01
	(2.68)	(2.61)	(3.62)	(1.26)	(2.20)	(1.71)	(0.05)
firm zero	0.01	−0.00	−0.00	−0.00**	−0.00	−0.02***	−0.05***
	(1.60)	(−1.31)	(−0.85)	(−2.55)	(−1.51)	(−2.78)	(−3.69)
bond zero	0.00***	−0.00	−0.00	−0.00***	−0.01	−0.04***	−0.01
	(3.66)	(−1.10)	(−1.32)	(−3.53)	(−1.54)	(−3.64)	(−0.96)
turnover	−0.31***	−0.31***	−0.17***	0.11	−0.90**	0.10	−0.53***
	(−16.98)	(−2.79)	(−4.14)	(1.15)	(−2.19)	(1.26)	(−5.11)
URC	6.91***	4.80***	11.86***	32.52***	55.20**	263.15***	35.91*
	(10.42)	(9.56)	(2.87)	(4.15)	(2.25)	(7.03)	(1.84)
Amihud risk	0.61***	0.01	0.89**	3.51***	9.63***	29.29***	3.24
	(2.68)	(0.61)	(2.16)	(3.54)	(3.16)	(6.54)	(1.02)
URC risk	1.91***	3.16	8.44***	28.02***	39.50**	214.27***	−37.86
	(12.75)	(1.03)	(2.58)	(4.92)	(2.08)	(6.38)	(−0.88)

Panel B: Marginal liquidity regressions, post-subprime (2007:Q2-2008:Q1)

	AAA	AA	A	BBB	BB	B	CCC
Amihud	2.01***	5.92	2.30	15.78	8.21	33.45***	4.96
	(6.51)	(1.26)	(0.48)	(0.98)	(0.68)	(3.52)	(0.87)
Roll	0.02***	0.08	0.07**	0.02	−0.07	0.04	−0.25
	(4.79)	(0.69)	(2.01)	(0.50)	(−0.42)	(0.33)	(−0.90)
firm zero	0.09	−0.00	−0.00**	−0.00	−0.04***	0.01	0.00
	(1.12)	(−0.92)	(−2.03)	(−1.31)	(−4.20)	(0.48)	(0.01)
bond zero	−0.00***	−0.00	−0.01**	−0.01	−0.06***	−0.02	−0.01
	(−2.67)	(−0.75)	(−2.03)	(−1.14)	(−14.95)	(−1.34)	(−1.35)
turnover	−0.41	0.11*	−0.52***	−3.20	11.11**	1.32	22.43**
	(−1.34)	(1.77)	(−2.83)	(−1.16)	(2.27)	(0.08)	(2.04)
URC	16.00***	47.71	9.44	21.14	150.98***	256.14*	95.84**
	(16.82)	(0.95)	(0.23)	(0.86)	(2.80)	(1.78)	(2.15)
Amihud risk	−0.00**	1.55	4.48	−1.17	5.44*	33.01**	10.64**
	(−2.41)	(1.42)	(1.12)	(−0.45)	(1.66)	(2.14)	(2.43)
URC risk	10.01	91.78	50.01*	27.61***	82.25	162.86***	132.67***
	(1.45)	(1.42)	(1.95)	(3.05)	(1.57)	(2.84)	(10.46)

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

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

where i is for bond in rating R and t is time measured in quarter. In total 56 regressions are run (8 liquidity variables × 7 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 $2005:Q1$ to $2008:Q1$. Panel A shows the coefficients using data before the Subprime crisis, while Panel B shows the coefficients using data after 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: Multivariate liquidity regressions, pre-subprime (2005:Q1-2007:Q1)

	AAA	AA	A	BBB	BB	B	CCC
intercept	−2.8***	0.2	−0.9***	2.3***	8.4***	5.7*	43.3***
	(−20.81)	(1.04)	(−3.02)	(2.71)	(3.23)	(1.80)	(2.95)
Amihud	0.70***	1.68*	2.91***	−4.18	1.34	13.04	25.24
	(2.83)	(1.88)	(4.84)	(−1.24)	(0.22)	(1.30)	(1.58)
Roll	0.05***	0.08***	0.07***	0.02	0.10**	−0.32*	−0.82
	(17.89)	(3.39)	(4.84)	(0.56)	(2.03)	(−1.86)	(−1.26)
bond zero	0.000***	0.000	0.001***	−0.004***	−0.017***	−0.019***	−0.035***
	(3.50)	(0.69)	(3.27)	(−3.22)	(−3.54)	(−4.00)	(−2.70)
turnover	−0.16***	−0.03	0.41***	−0.03	−2.07***	−0.07	−1.14*
	(−5.16)	(−0.20)	(4.13)	(−0.32)	(−4.31)	(−1.07)	(−1.82)
URC	−5.18***	1.89	9.92*	83.71***	40.12	192.18***	63.07***
	(−4.93)	(0.43)	(1.69)	(2.61)	(1.28)	(5.31)	(3.78)
Amihud risk	0.31***	−0.04	0.10	1.50*	6.48**	11.47***	3.14
	(27.64)	(−0.75)	(0.44)	(1.66)	(2.16)	(3.71)	(0.38)
URC risk	2.46**	−2.11	−2.64	−31.73*	−24.01	−37.27	−92.31
	(2.01)	(−0.52)	(−0.69)	(−1.76)	(−1.32)	(−0.85)	(−1.41)
age	0.000	−0.000	0.002	−0.009	0.039	−0.008	−0.183*
	(0.08)	(−0.05)	(0.74)	(−1.22)	(1.57)	(−0.32)	(−1.85)
coupon	−0.02***	−0.01	0.04***	−0.11***	−0.38***	−0.23***	−1.68*
	(−7.18)	(−0.94)	(3.94)	(−2.92)	(−3.40)	(−2.70)	(−1.95)
amount issued	0.01**	0.01**	0.01**	0.06***	0.14***	0.14*	0.51**
	(2.16)	(2.43)	(2.11)	(4.51)	(3.09)	(1.70)	(2.23)
10y swap	−0.081***	−0.034***	−0.048***	−0.052***	−0.151	−0.227	−2.298*
	(−5.59)	(−2.82)	(−3.94)	(−3.77)	(−1.37)	(−0.86)	(−1.83)
10y-2y swap	0.023**	−0.017	−0.022	−0.103***	−0.101	−0.949**	0.760
	(2.01)	(−1.22)	(−1.47)	(−5.63)	(−0.71)	(−2.15)	(0.54)
equity vol	0.015**	0.008***	0.009*	0.013***	0.027***	0.064**	0.097***
	(2.43)	(15.91)	(1.90)	(3.89)	(3.38)	(2.55)	(2.95)
pretax1	0.947***	0.007	0.009	−0.039**	−0.135***	0.092*	−0.087
	(16.26)	(0.58)	(0.44)	(−2.16)	(−3.50)	(1.81)	(−1.26)
pretax2	−0.183***	−0.011*	−0.016**	−0.015**	−0.011	0.256	0.000
	(−34.32)	(−1.72)	(−2.27)	(−1.98)	(−0.28)	(0.35)	(NaN)
pretax3	0.005	−0.004	0.001	0.025***	0.082***	−0.135	0.000
	(1.08)	(−1.54)	(0.42)	(3.64)	(2.82)	(−0.38)	(NaN)
pretax4	0.001	0.001	0.000	−0.039***	−0.017	0.000	0.000
	(0.56)	(0.54)	(0.17)	(−2.93)	(−1.15)	(NaN)	(NaN)
sales to income	−0.008***	−0.000	−0.001	−0.004*	−0.015*	−0.018	−0.052
	(−6.24)	(−0.50)	(−0.61)	(−1.77)	(−1.72)	(−1.52)	(−1.29)
long term debt to asset	−0.010***	−0.001*	0.001	0.010***	−0.018	−0.058***	0.060
	(−5.08)	(−1.76)	(1.13)	(3.57)	(−1.41)	(−3.35)	(0.47)
leverage ratio	0.013***	0.000	−0.001	0.000	0.024**	0.052***	−0.062
	(9.09)	(1.29)	(−0.74)	(0.06)	(1.97)	(4.69)	(−0.50)
time-to-maturity	0.015***	0.017***	0.021***	0.043***	0.051***	0.034**	0.134***
	(2.80)	(13.06)	(15.69)	(6.57)	(3.76)	(2.57)	(2.66)
N	491	1421	4227	1186	438	512	77
R^2	0.45	0.51	0.50	0.60	0.50	0.53	0.80

Table 3: Multivariate liquidity regressions. For each of the seven 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 2005:Q1 to 2007:Q1, while Panel B shows the results for data from 2007:Q2 to 2008:Q1. 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:Q2-2008:Q1)

	AAA	AA	A	BBB	BB	B	CCC
intercept	-2.2	-0.2	-0.8	8.6	11.8	11.0	14.8
	(-1.20)	(-0.32)	(-0.21)	(0.93)	(0.23)	(0.69)	(1.05)
Amihud	3.22^{***}	1.72	-1.22	34.58^{*}	-30.31	21.32	-7.23
	(2.67)	(0.47)	(-0.13)	(1.70)	(-0.50)	(1.19)	(-0.78)
Roll	0.11^{**}	-0.07	-0.02	0.06	-0.07	0.04	-0.29
	(2.18)	(-0.50)	(-0.14)	(0.56)	(-0.56)	(0.31)	(-0.55)
bond zero	0.001	-0.000	-0.010	-0.012	-0.050	-0.008	-0.012
	(0.70)	(-0.01)	(-1.37)	(-1.13)	(-1.04)	(-0.55)	(-0.90)
turnover	1.77^{***}	0.59	-0.63	-3.33	0.16	-0.54	0.28
	(3.47)	(0.49)	(-0.49)	(-0.91)	(0.03)	(-0.03)	(0.02)
URC	3.84	-27.36	-68.81	-141.68^{*}	421.00	-77.17	-54.60
	(0.33)	(-0.60)	(-1.45)	(-1.89)	(0.86)	(-0.39)	(-0.59)
Amihud risk	-0.00	1.11	6.06^{***}	-9.12^{***}	26.22	20.13	4.72
	(-1.60)	(0.81)	(4.58)	(-6.10)	(1.40)	(1.29)	(0.94)
URC risk	5.12	107.14	68.72^{*}	145.84^{***}	-381.12^{*}	114.26	142.38
	(0.51)	(1.09)	(1.76)	(3.48)	(-1.89)	(1.24)	(1.35)
age	-0.007	-0.018^{**}	0.035	-0.046	-0.038	-0.047	-0.000
	(-1.39)	(-2.00)	(1.08)	(-1.35)	(-0.18)	(-1.21)	(-0.00)
coupon	0.08^{**}	0.00	-0.12	-0.13	0.08	0.01	-1.02^{***}
	(2.36)	(0.05)	(-0.74)	(-0.49)	(0.05)	(0.01)	(-3.12)
amount issued	0.07^{***}	0.12^{***}	-0.00	0.15	0.23	0.22^{*}	0.23
	(3.03)	(19.67)	(-0.04)	(1.25)	(0.14)	(1.90)	(1.21)
10y swap	-0.002	-0.111	0.356	-0.918^{**}	-1.201	-1.956^{***}	-0.903
	(-0.01)	(-1.22)	(1.44)	(-2.57)	(-1.29)	(-4.47)	(-0.44)
10y-2y swap	0.122	0.273^{***}	0.108	-0.303	2.761^{***}	1.930^{***}	1.499
	(1.32)	(4.48)	(0.38)	(-0.69)	(4.24)	(12.94)	(0.85)
equity vol	0.046^{*}	0.034^{***}	0.131^{***}	0.063^{***}	-0.025	-0.044	0.163^{***}
	(1.86)	(3.15)	(5.76)	(9.21)	(-0.36)	(-1.25)	(4.58)
pretax1	0.000	-0.145^{***}	0.004	-0.219^{**}	-0.157	0.081	0.011
	(NaN)	(-9.40)	(0.05)	(-2.23)	(-0.13)	(1.40)	(0.12)
pretax2	0.000	0.055^{***}	-0.046^{***}	0.010	-0.217	0.000	0.000
	(NaN)	(8.40)	(-2.58)	(0.18)	(-0.17)	(NaN)	(NaN)
pretax3	-0.022	-0.044^{**}	0.008	-0.088	0.000	0.000	0.000
	(-0.12)	(-2.17)	(0.62)	(-1.49)	(NaN)	(NaN)	(NaN)
pretax4	0.002	0.038	-0.005	0.242^{*}	0.000	0.000	0.000
	(0.43)	(0.68)	(-0.42)	(1.68)	(NaN)	(NaN)	(NaN)
sales to income	-0.011	-0.000	-0.000	-0.027^{**}	0.001	-0.046	-0.234^{*}
	(-0.37)	(-0.32)	(-0.33)	(-1.97)	(0.04)	(-1.23)	(-1.89)
long term debt to asset	0.009	-0.006	0.021^{*}	0.071^{*}	0.088	-0.129^{*}	0.207^{**}
	(0.09)	(-1.00)	(1.76)	(1.67)	(1.05)	(-1.70)	(2.48)
leverage ratio	-0.011	-0.006^{**}	-0.034^{***}	-0.066	-0.141	0.141^{*}	-0.065^{*}
	(-0.09)	(-2.08)	(-3.23)	(-1.13)	(-1.55)	(1.84)	(-1.65)
time-to-maturity	0.013^{**}	-0.002	0.012^{*}	0.014	-0.010	0.015	0.060^{***}
	(1.97)	(-0.14)	(1.95)	(1.15)	(-0.08)	(0.30)	(3.11)
N	193	722	912	145	30	140	39
R^2	0.65	0.68	0.75	0.83	0.92	0.78	0.94

Table 3: continued.

Panel A: Liquidity component in basis points, pre-subprime (2005:Q1-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	2.2	1.7 (1.6;1.8)	1.9 (1.8;2.1)	2.8 (2.6;3.2)	147	168	176
AA	2.2	1.5 (1.1;3.4)	1.7 (1.3;3.5)	3.3 (2.2;5.5)	579	469	373
A	7.1	6.4 (2.9;10.1)	6.6 (3.2;10.2)	8.5 (5.1;12.4)	1498	1438	1289
BBB	13.8	10.6 (6.2;16.0)	14.3 (9.4;20.9)	16.5 (10.7;23.5)	449	253	484
BB	68.4	32.9 (19.9;45.8)	128.8 (52.0;193.5)	43.5 (26.8;61.6)	156	112	169
B	147.7	121.4 (91.9;143.8)	122.7 (103.1;156.9)	199.1 (161.8;229.6)	103	176	233
CCC	410.5	127.5 (94.8;197.2)	788.9 (150.8;1415.0)	315.2 (147.7;559.4)	12	10	55

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2008:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	9.0	9.8 (6.7;14.3)	6.1 (4.7;7.8)	11.1 (10.4;15.0)	58	74	61
AA	18.9	9.3 (4.5;23.0)	18.2 (4.9;38.6)	29.3 (7.4;57.9)	241	240	241
A	52.0	35.4 (14.0;80.6)	55.8 (25.0;91.2)	64.9 (32.0;110.4)	335	306	270
BBB	62.8	43.9 (15.0;92.1)	64.5 (26.6;199.0)	80.2 (25.5;145.2)	59	31	55
BB	180.7	82.7 (63.8;182.3)	365.5 (183.9;517.8)	93.8 (84.3;493.2)	10	7	13
B	120.0	83.0 (52.0;214.0)	110.4 (47.6;242.5)	166.6 (97.0;294.4)	48	45	47
CCC	63.9	21.0 (13.0;29.1)	46.9 (4.8;70.9)	123.7 (114.0;145.2)	3	3	33

Table 4: Liquidity Component in basis points. For each rating we run the pooled regression

$$Spread^R_{it} = \alpha + \overline{\gamma}\overline{L}_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where $\overline{L}_{it}$ is a vector of seven liquidity proxies. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we define for every observation in the bucket the liquidity score as $\overline{\gamma}\overline{L}_{it}$. The liquidity component in the bucket is defined as the 50% quantile minus 5% quanftile of the liquidity score. 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)

	0-2y	2-5y	5-30y
AAA	−36 (−146;−16)	83 (−811;128)	21 (17;28)
AA	−152 (−2612;7932)	64 (34;134)	15 (11;26)
A	126 (48;188)	61 (27;86)	25 (15;41)
BBB	45 (24;67)	45 (26;58)	21 (13;28)
BB	29 (18;47)	107 (38;154)	21 (13;29)
B	69 (41;92)	46 (37;57)	47 (42;60)
CCC	50 (33;87)	152 (26;270)	62 (28;116)

Panel B: Liquidity component in fraction of spread, post-subprime (2007:Q2-2008:Q1)

	0-2y	2-5y	5-30y
AAA	104 (55;235)	20 (15;31)	30 (28;43)
AA	68 (25;175)	40 (11;89)	44 (12;97)
A	115 (33;282)	105 (40;167)	76 (33;124)
BBB	85 (24;173)	72 (26;201)	53 (16;94)
BB	65 (42;149)	83 (54;113)	40 (38;202)
B	32 (19;75)	27 (12;59)	38 (22;62)
CCC	5 (3;6)	7 (1;10)	23 (19;29)

Table 5: Liquidity Component in fraction of spread. This table shows for every rating and maturity bucket the liquidity component in Table 4 divided by the 50% quantile spread to the swap rate. Confidence bands are found by a wild cluster bootstrap.

Panel A: Liquidity component in basis points, pre-subprime (2005:Q1-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	2.5	2.2 (1.6;3.0)	1.9 (1.7;2.5)	3.5 (2.4;3.0)	147	168	176
AA	4.0	3.1 (1.1;4.6)	3.5 (1.2;5.3)	5.3 (2.0;6.1)	579	469	373
A	3.8	2.3 (1.7;5.3)	3.4 (2.4;5.7)	5.6 (4.0;7.7)	1498	1438	1289
BBB	12.5	9.7 (5.1;16.4)	13.0 (7.8;19.4)	14.7 (9.1;21.4)	449	253	484
BB	38.8	25.6 (12.6;52.2)	67.1 (17.4;148.2)	23.7 (15.9;40.3)	156	112	169
B	163.4	148.9 (88.1;214.9)	151.9 (88.0;220.9)	189.4 (134.2;256.2)	103	176	233
CCC	256.6	64.1 (30.1;168.1)	551.6 (41.5;1275.5)	154.1 (70.6;421.2)	12	10	55

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2008:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	7.6	7.6 (7.2;11.4)	4.8 (4.3;6.3)	10.3 (9.1;15.1)	58	74	61
AA	13.7	8.6 (3.8;20.8)	12.7 (4.4;34.7)	19.9 (6.5;55.8)	241	240	241
A	25.3	15.9 (10.4;50.5)	22.6 (13.0;60.1)	37.3 (21.7;83.0)	335	306	270
BBB	61.3	37.7 (18.7;72.1)	67.2 (30.8;119.5)	79.0 (32.9;130.8)	59	31	55
BB	176.3	103.8 (27.6;218.2)	85.3 (25.1;209.1)	339.7 (100.1;713.0)	10	7	13
B	168.6	131.1 (66.4;270.1)	185.6 (66.9;302.8)	189.1 (92.0;333.5)	48	45	47
CCC	64.5	5.1 (2.2;19.0)	81.0 (5.2;148.5)	107.5 (84.3;165.8)	3	3	33

Table 6: Liquidity Component in basis points when the Treasury rate is used as riskfree rate. For each rating we run the pooled regression

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

where $\overline{L}_{it}$ is a vector of seven liquidity proxies. In all other tables the corporate bond spread is relative to the swap rate, but this table shows the estimated liquidity component when using the Treasury rate as riskfree rate. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we define for every observation in the bucket the liquidity score as $\overline{\gamma}\overline{L}_{it}$. The liquidity component in the bucket is defined as the 50% quantile minus 5% quantile of the liquidity score. 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 (2005:Q1-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	3.1	2.2 (100.0)	2.4 (100.0)	4.7 (100.0)	147	168	176
AA	2.7	2.3 (100.0)	2.2 (100.0)	3.6 (100.0)	579	469	373
A	4.1	3.2 (100.0)	3.6 (100.0)	5.5 (100.0)	1498	1438	1289
BBB	15.1	13.0 (100.0)	14.6 (100.0)	17.7 (100.0)	449	253	484
BB	38.4	32.4 (100.0)	43.3 (100.0)	39.3 (100.0)	156	112	169
B	150.2	132.4 (100.0)	140.8 (100.0)	177.3 (100.0)	103	176	233
CCC	160.1	117.8 (100.0)	200.8 (100.0)	161.6 (100.0)	12	10	55

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2008:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	15.4	25.7 (100.0)	10.2 (100.0)	10.3 (100.0)	58	74	61
AA	21.3	13.1 (100.0)	21.0 (100.0)	29.7 (100.0)	241	240	241
A	38.2	34.0 (100.0)	35.7 (100.0)	45.1 (100.0)	335	306	270
BBB	70.2	40.9 (100.0)	55.4 (100.0)	114.4 (100.0)	59	31	55
BB	368.0	226.4 (100.0)	463.4 (100.0)	414.1 (100.0)	10	7	13
B	174.0	155.4 (100.0)	174.2 (100.0)	192.5 (100.0)	48	45	47
CCC	69.7	9.5 (100.0)	83.6 (100.0)	116.1 (100.0)	3	3	33

Table 7: Liquidity Component in basis points with age and amount issued. For each rating we run the pooled regression

$$Spread^R_{it} = \alpha + \overline{\gamma}\overline{L}_{it} + \text{credit risk controls}_{it} + \epsilon_{it}$$

where $\overline{L}_{it}$ is a vector of 7 liquidity proxies plus age and amount issued. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we define for every observation in the bucket the liquidity score as $\overline{\gamma}\overline{L}_{it}$. The liquidity component in the bucket is defined as the 50% quantile minus 5%quantile of the liquidity score. 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 (2005:Q1-2007:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	4.1	2.6 (2.5;3.7)	2.8 (2.6;3.5)	7.0 (5.7;7.5)	147	168	176
AA	4.2	3.1 (1.7;6.2)	3.7 (1.9;6.6)	5.9 (3.5;9.6)	579	469	373
A	6.2	3.8 (2.9;7.3)	5.6 (4.1;8.7)	9.4 (6.7;12.9)	1498	1438	1289
BBB	20.4	16.5 (8.8;27.9)	21.4 (13.1;32.7)	23.2 (15.7;34.6)	449	253	484
BB	57.4	41.9 (17.7;85.2)	85.4 (28.8;162.1)	44.9 (28.6;73.5)	156	112	169
B	244.6	200.4 (134.4;279.6)	230.6 (161.0;301.4)	302.7 (264.8;354.9)	103	176	233
CCC	313.8	89.5 (31.9;219.7)	638.2 (79.5;1432.8)	213.8 (99.1;582.2)	12	10	55

Panel B: Liquidity component in basis points, post-subprime (2007:Q2-2008:Q1)

	average	0-2y	2-5y	5-30y	N 0-2y	N 2-5y	N 5-30y
AAA	15.2	19.0 (16.4;21.3)	9.2 (7.6;10.9)	17.3 (14.4;21.9)	58	74	61
AA	26.2	14.8 (5.3;30.5)	23.2 (6.4;50.3)	40.5 (10.6;78.6)	241	240	241
A	41.9	30.3 (16.2;60.9)	38.1 (22.1;69.1)	57.1 (32.4;96.9)	335	306	270
BBB	92.6	64.0 (37.2;112.5)	97.0 (52.8;187.5)	116.8 (54.6;190.1)	59	31	55
BB	169.4	101.5 (42.0;214.2)	103.6 (34.1;215.4)	303.2 (108.5;575.3)	10	7	13
B	216.6	175.9 (100.8;305.9)	201.3 (84.7;348.4)	272.6 (185.5;412.1)	48	45	47
CCC	96.9	30.9 (7.0;68.7)	126.5 (83.4;175.5)	133.4 (119.5;190.6)	3	3	33

Table 8: Liquidity Component in basis points for an illiquid bond. For each rating we run the pooled regression

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

where $\overline{L}_{it}$ is a vector of 7 liquidity proxies. Within each rating and maturity bucket (0-2y, 2-5y, and 5-30y) we define for every observation in the bucket the liquidity score as $\overline{\gamma}\overline{L}_{it}$. The liquidity component in the bucket is defined as the 75% quantile minus 5% quantile of the liquidity score. This table shows for all buckets the liquidity component with standard errors in parenthesis. Confidence bands are found by a wild cluster bootstrap.

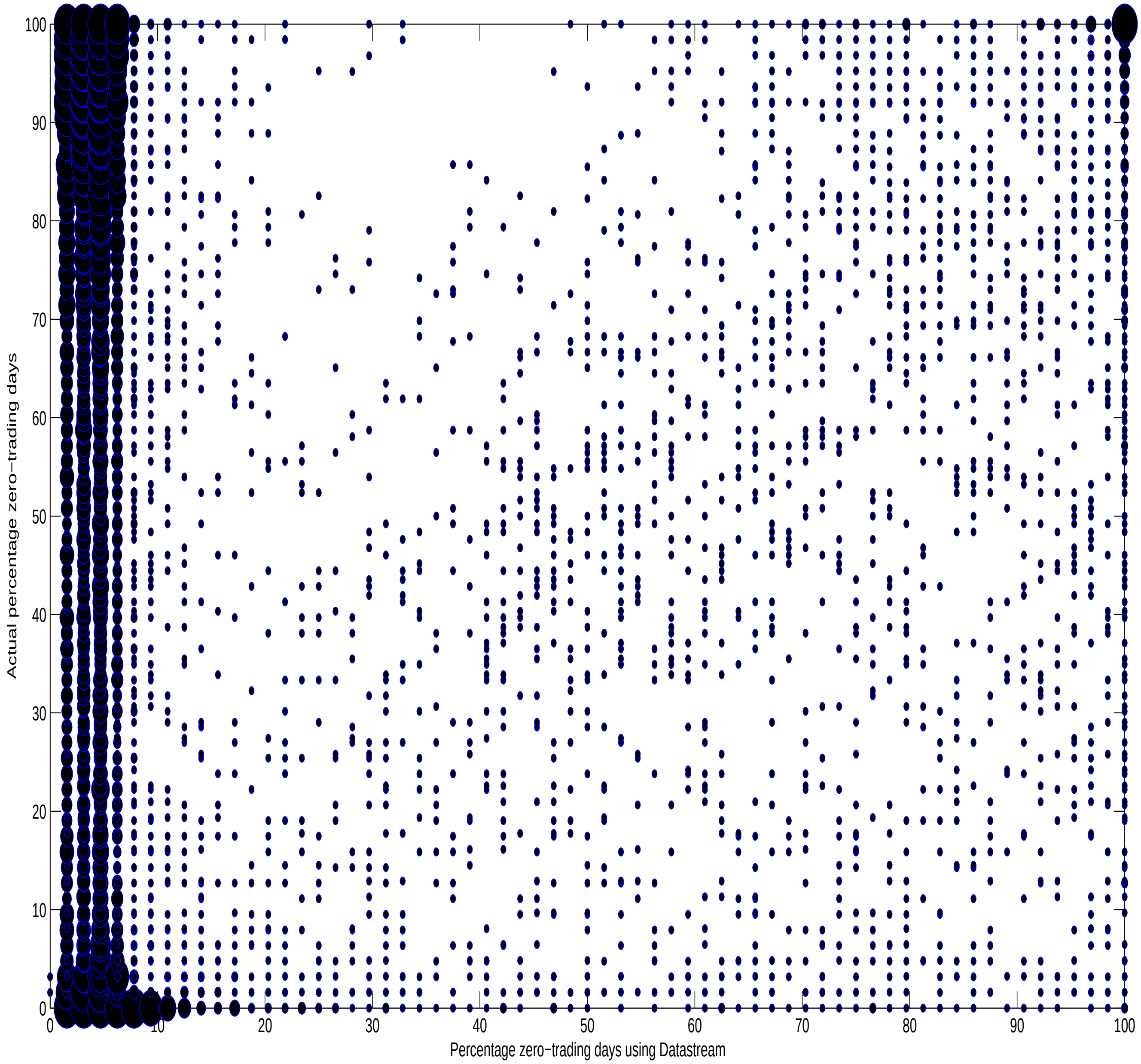

Figure 1: Zero-trading days using Datastream. This graph plots for every bond in the sample and every quarter from 2005:Q1 to 2007:Q4 the percentage zero-trading days using Datastream on the x-axis and actual percentage zero-trading days (based on all trades in TRACE) on the y-axis. The thickness of a point depends on the number of observations in that point. The total number of observations is 60,680.

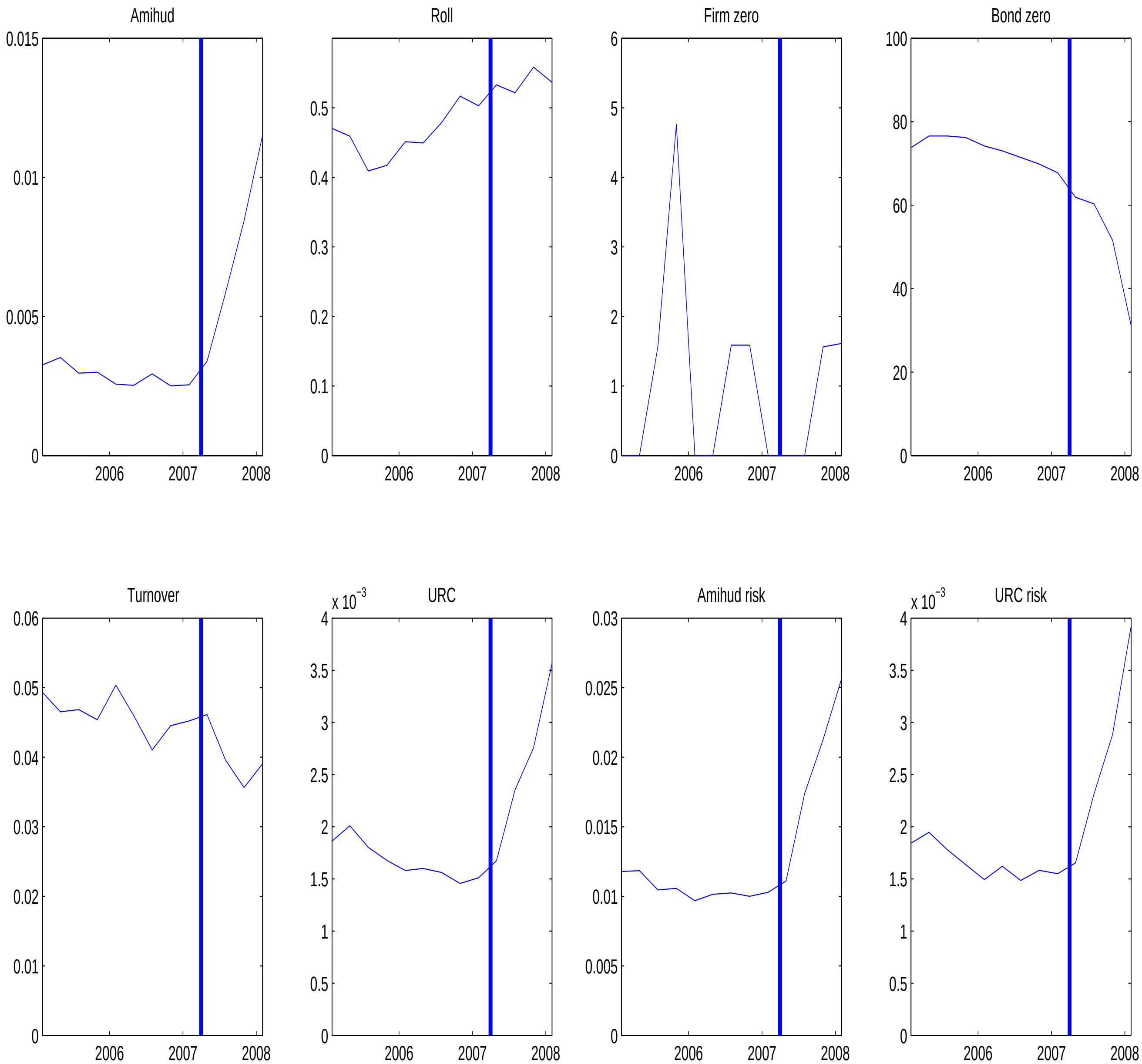

Figure 2: Time series of liquidity variables. This graph plots the time series of liquidity variables along with a line marking the start of the subprime crisis (beginning in 2007.Q2). Liquidity variables are measured quarterly.

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