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Effects of Liquidity on the Nondefault Component of Corporate Yield Spreads: Evidence from Intraday Transactions Data*

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Abstract

We estimate the nondefault component of corporate bond yield spreads and examine its relationship with bond liquidity. We measure bond liquidity using intraday transactions data and estimate the default component using the term structure of credit default swaps (CDS) spreads. With swap rate as the risk free rate, the estimated nondefault component is generally moderate but statistically significant for AA-, A-, and BBB-rated bonds and increasing in this order. With Treasury rate as the risk free rate, the estimated nondefault component is the largest in basis points for BBB-rated bonds but, as a fraction of yield spreads, it is the largest for AAA-rated bonds. Controlling for the unobservable firm heterogeneity, we find a positive and significant relationship between the nondefault component and illiquidity for investment-grade bonds but no significant relationship for speculative-grade bonds. We also find that the nondefault component comoves with indicators for macroeconomic conditions.

Keywords: Corporate Bond Yield Spreads, Credit Default Swaps, Liquidity, CDS-Bond Basis

JEL Classification: G12, G13, G14

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1. Introduction

To what extent do corporate bond yield spreads reflect default risk? How is the nondefault component of yield spreads, if it exists, associated with bond liquidity? These are fundamental issues to understanding how financial markets value corporate bonds and thus important for corporate financing, risk management, and monetary policy (Kohn, 2007). Early studies compared observed yield spreads to the spreads implied by bond pricing models calibrated using historical data on corporate bond defaults (e.g., Jones, Mason and Rosenfeld, 1984; Longstaff and Schwartz, 1995; Duffie and Singleton, 1997; Duffee, 1999; Elton, Gruber, Agrawal and Mann, 2001; Collin-Dufresne, Goldstein and Martin, 2001; Delianedis and Geske, 2001; Huang and Huang, 2003; Eom, Helwege and Huang, 2004). Their results are mixed. For example, Elton *et al.* (2001) suggested that, when taking into account both expected credit loss and associated risk premiums, most of yield spreads are attributable to default risk. In contrast, Huang and Huang (2003) suggested that the nondefault component accounts for the majority of yield spreads, especially so for high-rated investment-grade bonds. These conflicting results may be due largely to data limitations and model sensitivity in estimating the default component (Delianedis and Geske, 2001; Huang and Huang, 2003; Eom *et al.*, 2004).

To address these issues, recent studies examine the determinants of corporate bond yield spreads using data on credit default swap (CDS) spreads (e.g., Longstaff, Mithal and Neis, 2005; Nashikkar and Subrahmanyam, 2006; Ericsson, Reneby and Wang, 2007). They generally find that the majority of corporate yield spreads are due to default risk. To understand the advantage of using CDS data, a brief description of CDS is useful. A CDS is an insurance contract on credit risk, where a protection seller promises to buy the reference bond at its par value when a pre-defined credit event occurs. In return, a protection buyer makes periodic payments to the seller until the maturity date of the contract or until a credit event occurs. This periodic payment, usually expressed as a percentage of the notional value of protection, is called the “CDS spread”. Since default risk is traded through CDS separately from other factors that may affect bond price, such as embedded options, the CDS spread allows for a reasonable estimate for the default component of yield spread without explicitly estimating expected credit loss and associated risk premium.

In this paper we also use CDS spreads to estimate the default component of corporate bond yield spreads and examine the link between the nondefault component and liquidity. Our main contribution to the literature is our use of intraday transactions data to measure bond liquidity. Previous studies suggested that liquidity may manifest through the price impact of trades or market depth (e.g., Kyle, 1985), transaction costs (e.g., Acharya and Pedersen, 2005), or trading frequency (e.g., Vayanos, 1998; and Lo, Mamaysky and Wang, 2004). We explore a number of measures to capture each of these aspects of bond liquidity.[1] Importantly, our liquidity measures vary both across bonds and over time. By contrast, most existing studies used bond characteristics, such as coupon, size, maturity, and age, as proxies for bond liquidity (Fisher, 1959; Perraudin and Taylor, 2003; Houweling, Mentink and Vorst, 2005; Longstaff *et al.,* 2005; Ericsson *et al.,* 2007).[2] Interpreting the relation between bond spreads and these proxies may be complicated by the possible correlations between the proxies and the issuer's credit risk. In addition, while these proxies may vary across bonds, they are either constant or changing deterministically with the passage of time. Thus, they may not identify the effects of stochastic variation in bond liquidity on the nondefault component of yield spreads.

Our main results are based on swap rate as the risk free rate, as swap rate is widely believed to be closer to the risk free rate benchmark used by market participants in pricing corporate debt and its derivatives (e.g., Hull, Predescu and White, 2004; and Ericsson *et al.*, 2007). We find that the estimated nondefault component of yield spreads is statistically significant for only AA-, A-, and BBB-rated bonds and increasing in this order both in basis points and as a fraction of yield spreads. For speculative-grade bonds, the estimated nondefault components are generally insignificant. Among those statistically significant, the sizes of the estimated nondefault components are in general moderate – ranging from 3 basis points or 13 percent of yield spreads for AA-rated bonds to 24 basis points or 22 percent of yield spreads for BBB-rated bonds. Even so, our point estimates appear to be larger than those in existing studies, in particular for BBB-rated bonds. For example, Longstaff *et al.* (2005) found the nondefault components are statistically significant for A- and BBB-rated bonds, accounting respectively for about 10 and 6 percent of their yield spreads.

We also find that with Treasury rate as the risk free rate, the nondefault components are statistically significant for all investment-grade bonds (i.e., those rated AAA, AA, A, and BBB) and BB-rated bonds. In basis points, the nondefault component is the largest for BBB-rated bonds, about 60 basis points, and the smallest for AAA-rated bonds, about 32 basis points. As a fraction of yield spreads, the nondefault components are decreasing in bond rating, that is, the highest for AAA-rated bonds, 77 percent, and the lowest for BB-rated bonds, 17 percent. The nondefault components account for more than half of yield spreads for A- and higher-rated bonds, opposite to the empirical results in Elton *et al.* (2001), Longstaff *et al.* (2005) but consistent with the calibration results in Huang and Huang (2003).

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1 As detailed later, we present results with one liquidity measure in each of the three categories: price impact of trades based on Amihud (2002), estimated bid-ask spread based on Roll (1984), and turnover rate. Results with alternative measures, such as price dispersion and the number of trades, are similar and available upon request. A number of earlier papers studied bond liquidity based on rather limited transactions data, and they did not explicitly link them to the nondefault component of yield spreads (Alexander, Edwards and Ferri, 2004; Hong and Warga, 2000; Schultz, 2001; Hotchkiss and Ronen, 2002; Chakravarty and Sarkar, 2003; Hotchkiss and Jostiva, 2007).

2 Exceptions using time-varying measures for individual bond liquidity include Chen, Lesmond and Wei (2007), who used bid-ask spread of indicative quotes, the percentage of zero-returns, and estimated transaction costs, and recent studies by Chacko (2006), Mahanti, Nashikkar, Subrahmanyam, Chacko and Mallik (2006) and Nashikkar and Subrahmanyam (2006), who used "latent liquidity" – the weighted average turnover of funds holding the bond by their proportional holdings of the bond – to measure a bond's accessibility to market participants.

In our regression analysis, we link the nondefault component to our liquidity measures constructed from intraday transactions data. We find a positive and statistically significant relationship between the nondefault component of yield spreads and illiquidity for investment-grade bonds (i.e., those rated AA, A, and BBB) but no significant relationship for speculative-grade bonds. This result contrasts to Chen *et al.* (2007) who suggested the liquidity effects are stronger for speculative-grade bonds.[3] Our point estimates suggest that relative to total yield spreads, the liquidity effects decrease in rating – the strongest for AA-rated bonds and the weakest for BBB-rated bonds. Specifically, when one of our liquidity measures deteriorates by the magnitude of its interquartile range, the increase in the nondefault component can be as high as 6 percent of total yield spreads for AA-rated bonds, 4 percent for A-rated bonds, and 3 percent for BBB-rated bonds. While previous studies such as Longstaff *et al*. (2005) and Nashikkar and Subrahmanyam (2006) also suggested the nondefault component is positively related to illiquidity, they generally did not distinguish the liquidity effects by rating groups.[4]

We also find that the nondefault component of bond spreads comoves with indicators for macroeconomic conditions, particularly, negatively with the Treasury term structure. This result is consistent with previous studies suggesting that corporate yield spreads are associated with marketwide factors (Collin-Dufresne *et al.*, 2001; Duffie and Singleton, 1997; Delianedis and Geske, 2001; Liu, Longstaff and Mandell, 2006; Longstaff, 2004; Das and Hanouna, 2009). In addition, controlling for conventional liquidity proxies affects little the statistical significance of our transaction-based liquidity measures, suggesting our measures identify a unique part of the variation in the nondefault component of yield spreads. Finally, the estimated effects of our transaction-based liquidity measures are largely robust to a number of alternative model specifications and data samplings, such as restricting to firms included in the CDX indexes, excluding possibly news-driven trades, and using Treasury rate as the risk free rate.

The rest of the paper is organized as follows: Section 2 describes data sources and sampling schemes; Section 3 describes definitions and summary statistics of our transaction-based liquidity measures; Section 4 presents our methodology estimating the nondefault component of yield spreads and examines its cross-sectional and time-series properties; Section 5 reports our regression results on the effects of liquidity on the nondefault component; and Section 6 concludes.

[3] Chen *et al.* (2007) found that the effects of their liquidity measures on speculative-grade yield spreads are larger than those on investment-grade bonds. Because their studies did not explicitly decompose yield spreads into the default and nondefault components, the liquidity interpretation is complicated by the possible positive correlation between credit risk and illiquidity (Alexander *et al.*, 2004; Schultz, 2001; Ericsson and Renault, 2006). The same critique applies to other studies on the relation between yield spreads and illiquidity (e.g., Fisher, 1959; Perraudin and Taylor, 2003; and Houweling *et al.,* 2005).

[4] Previous studies also suggested that liquidity is a significant factor in multifactor bond pricing models (e.g., Downing, Underwood and Xing, 2005; Chacko, 2006; and de Jong and Driessen, 2006). There is also indirect evidence for bond illiquidity, as corporate bonds were found generally lagged behind CDS and equities in price discovery (e.g., Hotchkiss and Ronen, 2002; Norden and Weber, 2004; Blanco, Brennan and Marsh, 2005; and Zhu, 2006).

2. Data Description and Sampling

Our overall sample consists of bonds with data available on both bond prices and associated CDS spreads from January 1, 2001 to April 30, 2007. We use this sample to examine the cross-sectional and time-series properties of the nondefault component of yield spreads. To analyze the effect of liquidity on the nondefault component, we further merge the overall sample with intraday bond transactions data from NASD's TRACE (Trading Reporting and Compliance Engine) system, resulting in a smaller "regression sample." Throughout this paper, we conduct our analysis at the monthly frequency, where, unless noted otherwise, the monthly value of a time-varying variable is the average of its corresponding daily values. The rest of this section provides details on our data and sampling method.

2.1 The Overall Sample

The data on daily bond yields are from Merrill Lynch's Corporate Bond Index Database ("the ML Database").[5] The ML Database also contains information on some bond characteristics, including the amount of face value outstanding and a composite rating based on S&P and Moody's ratings. Additional bond descriptive information is obtained from both Bloomberg and Moody's DRS databases.[6] We retain only senior unsecured U.S. dollar-denominated bonds issued by U.S. firms that pay fixed semi-annual or zero coupons with remaining maturity less than 15 years. We also delete bonds that are callable, puttable, convertible, or have sinking fund features.[7]

We use issuer ticker to merge the bond yield data with the CDS spread data provided by Markit Partners. Issuer tickers are manually checked and adjusted to ensure the merge accuracy. The Markit's data contain daily composite spread quotes on CDS contracts with maturities at 6 month, 1, 2, 3, 5, 7, 10, 20, and 30 years.[8] Following the common practice, we use quotes corresponding to the modified restructuring clause for U.S. dollar-denominated notional values. In addition, a reference entity is included on any day

5 The yields are based on bid-side price quotes the close of business days. The main advantage of the ML Database is that it allows us to analyze the determinants of yield spreads back to 2001. In contrast, the comprehensive public dissemination of the TRACE transaction data started only in late 2004. The composition of the ML Database is rebalanced at the end of every month, at only which point may the Merrill's composite bond ratings change.

6 Moody's DRS database contains comprehensive information on the characteristics of corporate bonds ever rated by Moody's, including bond seniority, security, coupon frequency, issue date, and currency denomination. The database, though, has less information on option features written in the bond contracts, with which we use information searched on Bloomberg to complement.

7 More than half of the bonds in the ML Database are callable. Thus including those bonds would have increased our sample significantly. For bonds with option features, Merrill provides estimates of option-adjusted yields, or "effective yields". Using these effective yields and callability as an additional control variable, we repeated the analysis reported in this paper and obtained similar conclusions.

8 These composite quotes represent the average of the midpoint of bid and ask quotes from a number of major dealers. Markit calculates daily values only for contracts that have quotes from at least three different contributors after they filter out outliers, stale quotes, and flat curves.

only if its CDS quotes are non-missing at 1- and 10-year and at additional two or more of the four maturities in between.

As shown in Panel A of Table 1 (memo item), the overall sample consists of 1263 unique bonds from 328 firms (identified by unique issuer ticker), with on average nearly 4 bonds per firm. The numbers of bonds and firms vary significantly by bond rating. Slightly over three quarters of the sample are investment-grade bonds. Also, in term of number of bonds, A- and BBB-rated bonds are by far the most available; AA- and BB-rated bonds come next; and bonds in both tails of the rating distribution (i.e., AAA and CCC/below) are the fewest. In addition, excluding the tails of the rating distribution, the average number of bonds per firm increases with better rating, from slightly over 2 for B-rated bonds to about 10 for AA-rated bonds.

2.2 The Regression Sample

We use intraday transactions data provided by NASD's TRACE to compute measures for corporate bond liquidity. TRACE started to disseminate to the public intraday transactions data on July 1, 2002 for a small number of selected corporate bonds; but the dissemination expanded gradually and began to cover most of the corporate bonds traded over the counter on October 1, 2004 (see Appendix 1 for more details and the limitations of the TRACE data). The data contain trading information such as transaction price, trading size, settlement date and time. Following the practice in the existing studies using the TRACE data, we remove observations with “data errors” (e.g., Edwards, Harris and Piwowar, 2007).[9]

We first estimate daily liquidity measures and then compute their monthly average values, which in turn are merged with our overall sample using bond CUSIPs. The resultant “regression sample” is significantly smaller than the overall sample due mainly to the limited coverage of TRACE data before the full dissemination phase. As shown in Panel B of Table 1 (memo item), the regression sample consists of 808 unique bonds from 242 firms, with on average slightly over 3 bonds per firm. Even so, the distribution of the number of bonds by rating is similar to that in the overall sample. First, about 80 percent of the regression sample are investment-grade bonds. Second, most of investment-grade bonds are A- or BBB-rated, and most of speculative-grade bonds are BB-rated. Third, excluding the tails of rating categories, the average number of bonds per firm increases with better rating, from close to 2 for B-rated bonds to about 7 for AA-rated bonds.

[9] Specifically, we delete a trade if any one of the following conditions is met: trade size is missing or zero; price is less than $1 or greater than $500; price is more than 20 percent away from median price in a day; or price is more than 20 percent away from previous trading price.

2.3 Data on Risk Free Rates and Macroeconomic Variables

Our analysis focuses on the results with swap rate as the risk free rate. It is now widely believed that swap rate is closer to the risk free rate benchmark used by market participants in pricing corporate debt and its derivatives, in part because swaps face similar tax and regulatory treatments as corporate credits do (see, e.g., Hull *et al.*, 2004; Houweling and Vorst, 2005; Longstaff *et al.*, 2005; Blanco, Brennan and March, 2005; Zhu, 2006). In contrast, although Treasury securities are almost truly default free, Treasury yields may be affected by other factors, such as the specialness of Treasury securities and tax benefits.[10]

Nonetheless, we also contrast our main results with those using Treasury yields as the risk free rate, not only because some existing studies used Treasury yields but also because swap rate is not completely risk free due to the counterparty credit risk in the swap contract and the credit risk in the LIBOR rate.

We use the following conventional variables to measure macroeconomic conditions: the level and the slope of Treasury term structure, the return and implied volatilities on the S&P 500 index, and Treasury 10-year on-the-run premiums. These variables are collected from Bloomberg and the Federal Reserve Board.

3. Measuring Corporate Bond Liquidity Using Intraday Transactions Data

Using intraday transactions data for corporate bonds reported in TRACE, we compute one measure for each of the following three types of bond liquidity definitions: price impact of trades, transaction cost, and trading frequency.[11] Considering these multiple measures is important because different aspects of the liquidity concept may manifest in different fashion in the intraday trading statistics. We also discuss bond characteristics that are used in the literature as proxies for bond liquidity, and examine their relationship with our trading-based liquidity measures. Table 2 reports descriptive statistics for these liquidity measures.

3.1 Amihud Measure as Price Impact of Trades

Bond liquidity may manifest through the price impact of trades or market depth (Kyle, 1985). We adopt one of the most frequently-used price impact measures, proposed by Amihud (2002), by defining the

[10] For example, lower capital requirements for financial institutions to hold Treasury securities, hence higher demand for holding Treasury securities to fulfill regulatory requirements, may give additional values (convenience yield) to Treasuries beyond a pure risk-free instrument (Duffee, 1996; Reinhart and Sack, 2001). In addition, interests earned on Treasury securities are not taxed at the state level, but those on corporate bonds are.

[11] We also consider alternative measures for these definitions, such as modified Amihud measure, price dispersion, and average number of trades. Main results with these liquidity measures, available upon request, are qualitatively similar to what are reported here.

Amihud measure as the ratio of the absolute percentage change in bond price to the dollar size of a trade (in million dollars). That is, for each day t and bond i, we define

$$\text{Amihud}_t^i = \frac{1}{N_t^i}\sum_{j=1}^{N_t^i}\frac{\frac{|p_{j,t}^i - p_{j-1,t}^i|}{p_{j-1,t}^i}}{Q_{j,t}^i},$$

where $p_{j,t}^i$ (in dollars per \$100 par) and $Q_{j,t}^i$ (in million dollars) are the transaction price and the size of the trade, respectively.

The Amihud measure indicates illiquidity in that a larger value implies that a trade of a given size would move the price more, suggesting the bond is more illiquid. By construction, daily Amihud measures are nonmissing for only bonds traded at least twice on the day.

As shown on Line 1 of Table 2, for all rating categories together, the median Amihud measure is 0.34, suggesting that a median trade, at about $30,000 (Line 10), would move price by roughly 1 percent. By rating, the median Amihud measure is the highest for speculative-grade bonds, at 0.42, which is only modestly higher than those for other rating categories, all at about 0.32.

3.2 Estimated Bid-Ask Spread as Transaction Cost

Liquidity is also often defined by transaction costs (e.g., Amihud and Mendelson 1986; Acharya and Pedersen, 2005). A commonly-used measure for transaction costs is bid-ask spread. Unfortunately, our data do not have information on bid-ask quotes or on the side initiating a trade – which potentially could be used to trace out effective bid-ask spreads. Instead, we estimate bid-ask spreads using the well-known Roll (1984) model. Under certain assumptions, Roll showed that the effective bid-ask spread equals to the square root of the negative covariance between price changes in adjacent trades.[12] That is,

$$\text{BidAsk}_t^i = 2\sqrt{-\text{Cov}(\tilde{p}_{j,t}^i - \tilde{p}_{j-1,t}^i, \tilde{p}_{j-1,t}^i - \tilde{p}_{j-2,t}^i)},$$

where $\tilde{p}_{j,t}^i = \log p_{j,t}^i$.

[12] One key assumption is that the market is informationally efficient. That is, public information is instantaneously reflected in asset prices. The market microstructure literature has shown that the existence of asymmetric information and the associated risk of adverse selection affect the effective bid-ask spreads. To partly mitigate this issue, we conduct experiments in our robustness analysis by excluding trades that likely occur during major news hours.

The intuition of the Roll model is the following. Assuming informational efficiency and no news on a bond's fundamental values, bond prices should bounce up and down within the band formed by bid-ask quotes, generating a negative correlation between price changes in adjacent trades. The extent of this negative correlation depends on the the width of the band. By construction, daily bid-ask spread estimates are nonmissing for only bonds traded at least three times on the day.

As shown on Line 2 of Table 2, for all rating categories together, the median estimated bid-ask spread is 0.91 percent of price, rather costly comparing to trading stocks and Treasury securities (Chakravarty and Sarkar, 2003; Fleming, 2003; Hasbrouck, 2005). By rating, the median estimated bid-ask spreads increase with worse ratings, with the lowest at 0.8 percent of price for AA-rated bonds and the highest at 1.3 percent of price for speculative-grade bonds.

3.3 Turnover Rate as a Measure of Trading Frequency

Bond liquidity may also be reflected in trading frequency. Intuitively, all else equal, bonds that are more illiquid would trade less frequently. Trading frequency measures have been widely used as indicators for asset liquidity (see, e.g., Vayanos, 1998; Lo *et al.*, 2004; and Chen *et al.*, 2007). We consider monthly turnover rate as our trading frequency measure, which is the ratio of total trading volume in a month to the amount of face value outstanding. By construction, turnover rate statistics are nonmissing for all bonds in our sample.

As shown on Line 3 of Table 2, for all rating categories together, the median monthly turnover rate is merely 0.04, meaning that for the average bond in our sample, it takes about 25 months to turn over once. That corporate bonds are traded sparsely is also evident by other measures: the median number of traded days, Line 8, is 15 days, the median number of trades in a month, Line 9, is 44, and the median monthly trading volume, Line 11, is about $15 million.

There is no apparent difference by rating in the median turnover rate. While better-rated bonds tend to have higher median numbers of trades or traded days in a month, they are also generally larger in face values outstanding. For example, the median number of trades for AA-rated bonds is 100 times a month, notably larger than 35 times a month for speculative-grade bonds (Line 9); but the median size of AA-rated bonds is $800 million, also notably larger than just under $300 million for speculative-grade bonds (Line 7).

Table 3 shows pairwise correlations among the above three liquidity measures within each rating category. The correlations vary widely and are generally not particularly strong. Specifically, the correlations between the Amihud measure and bid-ask spread, are positive as expected, but they are less than 50 percent for all rating groups. The correlations between the Amihud measure and turnover rate are negative as expected, but they range from statistical insignificance for BBB-rated and speculative-grade bonds to only -8 percent for AA-rated bonds. The correlations between the bid-ask spread and turnover rate also vary widely, ranging from -4 percent for A-rated bonds to 8 percent for speculative-grade bonds.

The large variation in the correlations among these liquidity measures may reflect the multifaceted nature of the liquidity concept, suggesting that each of these measures may have captured only some aspects of bond liquidity. Thus, it would be helpful to combine these measures in our analysis to exploit their potential complimentary features.

3.4 Bond Characteristics as Proxies for Liquidity

Lacking of intraday transactions data, previous studies often use bond characteristics as proxies for bond liquidity, such as coupon rate, bond age, remaining maturity, and bond size. To save space, we don't recite the various hypotheses that are proposed in the literature on why these proxies may be reasonable. See, for example, Longstaff *et al.* (2005) for a reference.

Average bond characteristics are shown on Lines 4 to 7 of Table 2. For the entire regression sample, the median bond in a typical month has a coupon rate of 6.4 percent, is close to 4 years since issuance, has slightly over 4 years of remaining maturity, and has $400 million dollars outstanding. Not surprisingly, the median coupon rate increases with worse bond rating. In addition, speculative-grade bonds tend to be smaller and notably older in our sample, but the remaining maturity is the longest for BBB-rated bonds and the shortest for A-rated bonds .

3.5 Relationship between Liquidity Measures and Bond Characteristics

As argued earlier, bond characteristics used as proxies for liquidity are either constant or deterministic. So we cannot use them to identify time-varying liquidity effects from other stochastic shocks in the nondefault component. To help assess later to what extent our transaction-based liquidity measures contribute to our understanding of the stochastic variation in the nondefault component, we use a regression approach to analyze the relationship between our liquidity measures and bond liquidity proxies. Specifically, we regress each of our liquidity measures on coupon, bond size, and 4-th order polynomials of both bond age and remaining maturity. The function forms for bond age and remaining maturity are chosen to address possible nonlinear effects suggested by existing studies. See, for example, Edwards *et al.* (2007) and Hotchkiss and Jostova (2007).[13] In addition, we include firm and time fixed-effects to account for unobservable firm heterogeneity and macroeconomic effects.

[13] We have also conducted experiments with dummy variables indicating each year (up to 15) of bond age and remaining maturity and experiments with dummy variables indicating brackets of bond age and remaining maturity using conventional cutoff points at 1, 3, 5, 7, and 10 years. The results are similar to what we report here.

Table 4 presents the regression results. Note that our results on the Amihud and bid-ask spread measures are new to the literature and that those on the turnover rate measure are in general consistent with the evidence in the existing literature (Alexander *et al.*, 2004; Hotchkiss and Ronen, 2002; Edwards *et al.*, 2007; Downing *et al.*, 2005). The following findings are worth mentioning. First, our transaction-based liquidity measures are weakly related to bond characteristics, especially for lower rated bonds. Specifically, R^2s are modest, from 11 to 36 percent, and generally decreasing with lower ratings. The weak correlation suggests that our liquidity measures and bond characteristics may have captured different aspects of bond liquidity, especially for the lower rated bonds. Second, relationships between different transaction-based liquidity measures and bond characteristics don't necessarily follow the same directions. For example, bonds with larger coupon or smaller size are more liquid by the Amihud measure but less liquid by the turnover rate measure. Again, this points to the multifaceted nature of bond liquidity. Third, as for bond age and remaining maturity, the coefficients on their polynomials are jointly statistically significant at the 95 percent confidence level in all specifications. In general, the point estimates suggest that bonds that are older or have longer remaining maturities are more illiquid.

4. The Nondefault Component of Yield Spreads

In this section, we first describe our method of using the CDS term-structure to estimate the nondefault component of corporate bond yield spreads. We then examine the properties of the estimated nondefault component in both cross section and time series.

4.1 Estimation Method

The key issue of estimating the nondefault component of corporate bond yield spreads is to estimate appropriately the default component. Broadly speaking, there are two approaches to estimating the default component: one based on corporate bond pricing models, and the other based on CDS spreads. Typically, the former approach first calibrates a corporate bond pricing model to match historical data on corporate bond default frequency and loss given default, then uses the yield spread implied by the model as the estimate for the default component of the observed yield spread (e.g., Huang and Huang, 2003). This approach has two main drawbacks: one, the estimates are sensitive to the model assumptions on both default process and risk premium (Delianedis and Geske, 2001; Huang and Huang, 2003; Eom *et al.*, 2004); two, it is difficult, if not impossible, to estimate expected credit loss on individual bonds with reasonable precision. Estimations using aggregate default data ignore completely the heterogeneous risk profiles among different bonds, and they may have significant statistical errors because historical default events are sparse and clustered in a small number of recession periods.

The CDS-based approach avoids these potential problems because CDS spreads reflect market expectations on both default probability and loss given default and the associated risk premiums. As shown in Duffie (1999), under certain conditions, CDS spreads are equal to the yield spread on a bond with the same credit risk exposure. Due to data limitations, most existing studies use only 5-year CDS spread data (e.g., Longstaff *et al.,* 2005; Blanco, Brennan and March, 2005; Zhu, 2006; Nashikkar and Subrahmanyam, 2006; and Ericsson *et al.,* 2007). Of course, it is rare for a reference entity to have a bond maturing in exact 5 years on any given day. As a result, researchers rely on pricing information on the bonds straddling the 5-year maturity to estimate the yield spread on a hypothetical bond at the 5-year maturity. This may induce an estimation error because the reference entity might have issued a 5-year bond with different terms and the price on the 5-year hypothetical bond might have been different if it were actually traded. In addition, it is hard to fully address the coupon effect in bond yield computations, partly because the cash flow of the hypothetical bond is not well defined. Also, because there are no observable data on the hypothetical bond for either liquidity proxies or transactions data, statistical analysis on the liquidity effect has to be done using the bonds in the bracket.

We also use CDS data to estimate the default component of yield spreads, and our approach avoids constructing any hypothetical bonds and addresses the issues of both maturity mismatch and coupon effect. Our estimation has three steps. First, for each firm on each day, we estimate a CDS-implied par yield curve by adding swap rates to CDS spreads at observed maturity points and interpolating across maturities using the piecewise cubic Hermite interpolating polynomial (PCHIP) algorithm.[14] Under certain conditions laid out in Duffie (1999) and assuming swap rate is the appropriate measure of risk free rate, the resulting curve equals the par yield curve for floating-rate bonds with the same credit profile as the reference entity. Duffie and Liu (2001) further show that par yields on floating-rate and fixed-rate bonds by the same issuer would differ only a bit for the usual range of interest rate term structures and term to maturities (see also Longstaff *et al.,* 2005; and Nashikkar and Subrahmanyam, 2006). Thus, we use the resulting curve as a reasonable approximation for the par-yield curve for fixed-rate bonds with the same credit profiles.[15]

Second, from a firm's CDS-implied par yield curve, we compute zero yield curve and discount rate curve using the standard bootstrap method. Finally, we use the estimated discount rate curve to discount the cash flow of each bond and obtain an estimate of the bond price implied by the firm's CDS term structure. We call the yield computed from the resulting bond price “the CDS-implied yield”. The default component of bond yield spread is simply the CDS-implied yield minus the risk free rate, and the nondefault component is bond yield spread minus the default component.

[14] Both swap and Treasury rates are par yields estimated by the Board staff using the methodology outlined in Gurkaynak, Sack and Wright (2006). The PCHIP algorithm, available in Matlab, differs from a regular spline method in that it preserves the shape of the data and respects monotonicity. That is, on intervals where the data are monotonic, so is the interpolated curve; at points where the data have a local extremum, so does the interpolated curve. Therefore, PCHIP does not introduce artificial oscillations p between points, which a regular spline algorithm may often do.

[15] Longstaff *et al.* (2005) used a reduced-form CDS pricing model to reduce the approximation errors, and they echo Duffie and Liu (2001) that such errors may be small. Moreover, such model-based correction may not be desirable as the estimation errors may be sensitive to the specifications of CDS pricing models (see e.g., Ericsson *et al.,* 2007; and Huang and Zhou, 2007).

It is important to note the actual bond yield and the CDS-implied yield have identical cash flows. Thus, we remove both maturity mismatch and coupon effect in calculating both default and nondefault components of yield spread. Moreover, our approach implies that on any given period when a firm has multiple bonds meeting our sampling criteria, they are all kept in our sample. As discussed in details below, these extra degrees of freedom allow us to apply a fixed-effects approach to control for the unobservable firm heterogeneity, which effectively identifies the liquidity effect using variation across bonds by the same issuer.

Similar to our approach, Levin, Perli and Zakrajsek (2007) also utilize the full term structure of CDS spreads to estimate default component of bond yield spreads. However, while they match maturity for existing bonds, they fail to address the coupon effect issue, because they read the default component directly from the CDS term structure without taking into individual bond's cash flow. Also, our estimation of nondefault component resembles the (negative) CDS-cash bond basis in existing studies (e.g., De Wit, 2006; and Calamaro, Alam, Thakkar and Crnja, 2008), with the small difference reflecting our desire to follow closely the existing academic literature on the liquidity effect on bond yield spreads.

4.2 Cross-Sectional Characteristics

We examine the cross-sectional characteristics of the components of yield spreads for a sample of bonds with relatively stable risk profile during the period. Specifically, we remove bonds whose ratings ever changed by one or more whole rating letter and bonds that appear in less than three months over the period.[16] For each bond, we then compute its average yield spread and average default and nondefault components over the entire period. This results in a pure cross-sectional sample, consisting of 743 investment-grade bonds and 111 speculative-grade bonds.

Table 5 reports by bond rating the average values of yield spread and its components. Column (1) shows the average spread of bond yield over comparable-maturity swap rate. Columns (2) and (3) show, respectively, the default and nondefault components of the spread. Column (4) calculates the nondefault component as a fraction of yield spreads. Several patterns emerge from the table. First, not surprisingly, both yield spread and the default component increase with worse rating, from under 10 basis points for AAA-rated bonds to over 10 percent for CC-rated bonds. Second, the nondefault component, both in basis points and as a fraction of yield spreads, is statistically significantly different from zero for all but AAA-rated investment-grade bonds, with their sizes *increasing* with worse rating. In term of economic magnitude, the nondefault component is moderate in general, ranging 3 basis points, or 13 percent of yield spreads, for AA-rated bonds to 24 basis points, or 22 percent of yield spreads, for BBB-rated bonds.

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16 An alternative approach is to treat a bond with different ratings as different bonds. The results are similar to what we report here. The choice of three months is ad hoc. But the results with more restricted sampling such as by removing bonds that appear in less than up to 12 months are similar. The results without such restriction at all are also similar except for BB-rated bonds.

Even so, they are still notably larger than those in Longstaff *et al.* (2005), which, in contrast, found that nondefault components are insignificant for AAA/AA-rated bonds and *decrease* with worse rating (in particular, only 6 percent for BBB-rated bonds). Third, the nondefault components are statistically insignificantly different from zero for all but B-rated speculative-grade bonds. Notably, except for BB-rated bonds, these nondefault components are all negative. Fourth, for all investment-grade bonds together, the nondefault component averages 12 basis points and accounts for about 20 percent of yield spreads, while for speculative-grade bonds, the nondefault component is not significantly different from zero.

Columns (5)-(8) repeat the same exercises with Treasury-rate as the risk free rate measure. The results contrast to those with swap rate in several aspects. First, the nondefault components, both in basis points and as a fraction of yield spreads are statistically significantly different from zero for all investment-grade rating categories and, as a fraction of yield spreads, *decrease* with worse ratings. In particular, the nondefault components account for more than half of yield spreads for A- or better-rated bonds, and just over 40 percent of yield spreads for BBB-rated bonds. This contrasts to the result in Longstaff *et al.* (2005), which found that the nondefault components are less than half of yield spreads for all investment-grade bonds when using Treasury rate as the risk free rate. Second, the nondefault components are statistically significant for BB-rated bonds, accounting for 17 percent of yield spreads, but insignificant for other speculative-grade bonds. The results for BB-rated bonds are close to those found in Huang and Huang (2003) and Longstaff *et al.* (2005). Third, for all investment-grade bonds together, the nondefault component accounts for nearly half of spreads; while for speculative-grade bonds, the nondefault component is less than 10 percent of yield spreads. Both averages are statistically different from zero.

It is interesting to note that the choice of different risk free rate does not have much impact on the default component estimates (i.e., Columns (2) and (6)). That is, the different patterns of the nondefault components with alternative risk free rates reflect mostly the differences in yield spreads due to the factors causing the divergence between Treasury and swap rates, such as Treasury specialness and tax benefits. To the extent that these factors do not vary with corporate bond ratings, their effects account for a bigger part of yield spreads for higher-rated investment-grade bonds because their yield spreads are already low.

After having examined the means, Figure 1 plots by bond rating the histograms of the average nondefault component with swap rate as the risk free rate measure. We group all speculative-grade bonds except the CC-rated bond into a single category and don't show AAA-rated bonds due to their small sample sizes. A striking pattern of these histograms is that for each rating category, the density of the the nondefault component all peaks at nearly zero basis point. In addition, while the distributions are fairly narrow for AA- and A-rated bonds with right skewness, they are rather flat and fat-tailed for BBB-rated and, especially, speculative-grade bonds.

4.3 Time-Series Characteristics

Figure 2 plots by bond rating the median values of the monthly nondefault component for the bonds in the overall sample.[17] The top panel uses swap rate as the risk free rate. Several points are worth to note. First, as we have seen in the cross-sectional analysis, the nondefault component for BBB-rated bonds, dotted line, was almost always the highest among all rating categories. In addition, it declined notably from about 30 basis points in 2001 to about zero in early 2004 and then trended slightly up since 2006. Second, before 2004, the nondefault component for A-rated bonds, averaging 10 basis points, was generally higher than that for AA-rated bonds, averaging just below zero. However, since 2004, the two series became statistically indifferent; and both trended slightly up since 2006. Third, the nondefault component for speculative-grade bonds appeared to be volatile before 2003, due mainly to the small number of bonds in the early period (from about 10 bonds in early 2001 to about 60 bonds at the end of 2002). Since 2003, it had fluctuated around zero and fallen below zero in 2007.

The time series of nondefault component with Treasury rate, plotted in the lower panel of Figure 2, show similar patterns to those with swap rate, but with two notable differences. First, all series shifted upward; Second, we see more clearly a secular decline in the nondefault components for all investment-grade bonds from 2001 to 2004 and a gradual pickup since 2005.

4.4 Discussions

The above examinations of our estimated nondefault component of bond yield spreads raise a few research questions. First, the large variation in the estimated nondefault component, in both cross section and time series, beg for answers to what economic forces drive the nondefault component. In particular, we want to know to what extent the variation in the nondefault component are attributable to the cross-sectional or the stochastic variation in corporate bond liquidity. Second, there may be violations of the underlying assumptions in using CDS term structure to estimate the default component. Notably, the negative nondefault component we observed in both cross section and time series suggests that the CDS market may not be entirely liquid (Tang and Yan, 2007; Fulop and Lescourret, 2007) or that corporate bond and CDS markets don't react to credit news in a synchronized fashion (Blanco, Brennan and Marsh, 2005; Zhu, 2006).[18] Below we discuss these issues further and develop an empirical strategy to mitigate their impacts on our analysis.

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17 Time series plots of the mean values of the monthly nondefault component are similar to those of the median values for all but speculative-grade bonds. Due to their small numbers, the mean values for speculative-grade bonds exhibit even more volatilities in the early part of the studying period.

18 Counterparty credit risk in CDS may also bias our estimations of the default component. The effect of counterparty credit risk on CDS pricing is believed to be small during usual times because only highly-rated agents are able to sell default protections and margin requirements are imposed for the issues. Other factors, such as cheap-to-deliver option in CDS contracts, may also affect CDS-based estimates of the default component (see, e.g., Calamaro *et al.*, 2008). Assessing the importance of many of these factors is important especially in light of current financial turmoil, and we leave this for future research.

5. Effects of Liquidity on the Nondefault Component of Yield Spreads

We now report regression results on the effects of bond liquidity on the nondefault component of yield spreads. First, we demonstrate the importance of controlling for unobservable firm heterogeneity in identifying the liquidity effect. Second, we show that controlling for CDS liquidity and bond market informational efficiency increases significantly both the model fit and the economic significance of liquidity effects. Finally, we present a number of exercises that check for the robustness of our results. These exercises include (1) mitigating CDS liquidity issues by restricting our sample to only bonds issued by firms included in CDX indexes; (2) including bond characteristics as additional liquidity proxies; (3) explicitly controlling for macroeconomic conditions; (4) mitigating the impacts of news on our transaction-based liquidity measures by estimating our measures using trades outside major news hours; (5) using Treasury rate as the risk free rate measure in estimating the nondefault component; and (6) using nondefault component estimated without correcting coupon effects.

Note that, unless specified otherwise, the risk free rate used in the nondefault component estimation is swap rate. In addition, to reduce the impact of outliers, we windsorize the sample at 5 percent of both the nondefault component and liquidity measures used in each regression. We also use log scale for our liquidity measures in all regressions.

5.1 Controlling for Unobservable Firm Heterogeneity

Table 6 reports the results from OLS regressions of the nondefault component for four broad rating categories, including AA (AA-, AA, AA+), A (A-, A, A+), BBB (BBB-, BBB, BBB+), and speculative-grade (below BBB-). For each rating sample, we estimate the following models:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{time fixed effects} + \varepsilon. \quad (1)$$

We first use each of our three transaction-based liquidity measures individually, and then all three measures together. The time fixed effects control for macroeconomic conditions. Standard errors of the estimated coefficients are computed using the Huber/White robust method assuming that regression residual terms may be correlated across bonds issued by the same firm but uncorrelated across firms.

The results lend some support for the liquidity effect. Specifically, consistent with the common view, the coefficients on turnover rates are all negative, and statistically significant at the 95 percent confidence level for six out of eight regressions. The coefficients on the Amihud illiquidity measure and bid-ask spread are positive for only AA- and A-rated bonds and statistical significance in only some regressions (Columns 1 and 4 for the Amihud measure, Columns 2 and 6 for bid-ask spread). However, the coefficients on the Amihud illiquidity and bid-ask spread measures are all negative for BBB-rated and speculated-grade bonds, although none is statistically significant. The R^2 statistics for all regressions are modest: when all three liquidity measures are included at the same time, R^2 ranges from 10 percent for speculative-grade bonds to 36 for BBB-rated bonds.

A potential issue with the above OLS regressions is that the nondefault component may be affected by unobservable firm characteristics correlated with our liquidity measures, in which case an omitted variable bias occurs and the direction of bias is unpredictable (Chen *et al.,* 2007). An example of such unobservable heterogeneity is the "clientele effect". That is, institutional investors may form their bond portfolios based on certain firm characteristics that may be correlated with either credit risk or liquidity. Transactions by these investors in turn may generate liquidity impacts on yield spreads or on the nondefault component (see, e.g., Chacko, 2006; Mahanti *et al.,* 2006; and Nashikkar and Subrahmanyam, 2006). To address this issue, we add firm fixed-effects to the models in (1). That is, our model specifications become:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{firm and time fixed effects} + \varepsilon. \quad (2)$$

With the fixed-effects model, we now effectively identify the liquidity effect using the variation across bonds issued by the same firm. The richness of our data, especially the full term structure of CDS spreads allowing for multiple bonds by the same firm, gives us enough degrees of freedom to estimate these fixed-effects models.

As shown in Table 7, overall, controlling for the unobservable firm heterogeneity leads to stronger support for the liquidity effect on the nondefault component, especially for investment-grade bonds. Specifically, comparing to Table 6, the main change is that the coefficients on the Amihud illiquidity and bid-ask spread measures become positive and statistically significant at the 95 percent confidence level for AA- and A-rated bonds. In addition, results on turnover rate now show significant liquidity effects in all regressions. But the signs of the coefficients on the Amihud illiquidity and bid-ask spread measures remain mostly negative for both BBB-rated and speculative-grade bonds and even become statistically significant.

5.2 Controlling for CDS Liquidity and Bond Market Informational Efficiency

The reliability of using CDS spreads to estimate the default component of yield spreads depends on two critical assumptions. First, CDS spreads reflect solely credit risk and the associated risk premium. This assumption may be violated if CDS market is not perfectly liquid. While the CDS market may be more liquid than the cash market, partly due to the absence of short-sale constraints and its unfunded nature (Hull *et al.*, 2004; Longstaff *et al.*, 2005) its liquidity may have been varying over time and across firms.

Indeed, some recent studies suggest that the effect of CDS illiquidity on CDS spreads may be positive and statistically significant (Tang and Yan, 2007; Fulop and Lescourret, 2007). Thus, in the presence of CDS illiquidity, our CDS-based method may result in underestimated nondefault component. Put it differently, our estimated nondefault component would be negatively (positively) correlated with a CDS illiquidity (liquidity) measure. Empirically, it implies that all else equal, if liquidity conditions in bond and CDS markets are (positively) correlated, not controlling for CDS illiquidity results in (downward) biased estimates on the effect of bond illiquidity on the nondefault component of yield spreads.

Second, we assume that both the CDS and bond markets are similarly informational efficient in the sense that bond prices react to the news on credit risk as quickly as CDS spreads do. Recent studies suggest that bond markets may lag behind CDS in price discovery, possibly caused by, among other things, the short-selling constraint or higher transaction costs on corporate bonds (Blanco, Brennan and Marsh, 2005; Zhu, 2006). Specifically, when the issuer's credit quality deteriorates (improves), bond markets may have priced too little (much) spreads relative to CDS spreads, resulting in underestimation (overestimation) of the nondefault component. Empirically, this suggests that without controlling for the less informational efficiency in the bond markets, our estimated nondefault component would have a bias that is increasing in the issuer's credit quality.

To address the above issues, we add two CDS variables to (2) to control for CDS liquidity and the difference in the informational efficiency between the bond and CDS markets: First, in the absence of direct CDS liquidity measures, e.g., CDS bid-ask spreads, we use the number of quotes on 5-year CDS contracts to control for the CDS liquidity effect. Presumably, a larger number of quotes indicates more dealers making the market, thus improving the CDS liquidity. Thus, our discussion above implies the coefficient on the number of quotes is expected to be positive. Second, instead of trying to measure directly the difference in the informational efficiency between the two markets, we include the one-period lagged CDS spread as a measure for the issuer's credit condition to control directly for the potential bias. This variable is read at the corresponding bond's maturity from the CDS term structure fitted using the PCHIP algorithm described above. Our discussions above suggest that all else equal, the coefficients on the lagged CDS spread are expected to be negative. We call these two variables as CDS liquidity proxies, and our models become

$$\begin{aligned}\text{Nondefault spreads} = \; & c + \alpha \log(\text{bond [il]liquidity measures}) + \text{CDS liquidity proxies} \\ & + \text{firm and time fixed effects} + \varepsilon.\end{aligned} \tag{3}$$

The results with these two additional controls are shown in Table 8. Overall, controlling for CDS liquidity results in firmer support for the liquidity effect – in terms of coefficient signs, statistical significance, and model fit – especially for investment-grade bonds. First, all coefficients on the liquidity measures for BBB-rated bonds now have expected signs and statistically significant at the 95 percent confidence level.

Second, except for AA-rated bonds, all coefficients on the lagged CDS spread are negative as expected and mostly statistically significant. This suggests that all else equal, the nondefault component of yield spreads increases with the improvement in the issuer's credit quality, consistent with the less informational efficiency in the bond markets. Third, except for AA-rated bonds, all coefficients of the number of CDS quotes are positive as expected but only statistically significant for the A-rated and some BBB-rated regressions, generally consistent with the existence of CDS illiquidity. Fourth, notably, the R^2 statistics increase significantly across all specifications but most dramatically for the speculative-grade bonds.

To examine the economic magnitude of the liquidity effect, we use the point estimates in Table 8 to calculate how the nondefault components change when each of the liquidity measures changes from its 25th to 75th percentile. We only report those estimates being statistically significant. The results are stated in Table 9. Overall, in basis points, turnover rate has the largest impact, ranging from -1.5 to -2.8 basis points; bid-ask spread comes the second, about 1 to 2 bps; and the Amihud measure is slightly smaller, about 0.5 to 1.5 bps. Relative to the median yield spreads for our overall samples, the liquidity effects range from 1.5 to 6 percent (in absolute values). In addition, relative to total yield spreads, the liquidity effects decrease in rating – the strongest for AA-rated bonds and the weakest for BBB-rated bonds. Specifically, when the liquidity measures deteriorate by the magnitude of their interquartile ranges, the increase in the nondefault component can be as high as 6 percent of total yield spreads for AA-rated bonds, 4 percent for A-rated bonds, and 3 percent for BBB-rated bonds. These results suggest that the liquidity effects appear to be quantitatively moderate but nontrivial both relative to the near-zero nondefault components and even to their full yield spreads.

5.3 Robustness Analysis

5.3.1 Sample with CDX Members Only

To further mitigate the possible impact of CDS market liquidity on our estimations of nondefault component, we now examine the set of firms that are members of the CDX indexes at the time of trading. The CDS contracts of these firms are likely more liquid than other contracts because of more exposures and more trades by the index arbitrage activities. While this does not guarantee to eliminate the issue of CDS liquidity creeping into our estimation of the nondefault component, it mitigates its impact on the cross-sectional effect of bond liquidity on the nondefault component.

Table 10 reports the regression results with CDX members. The restriction greatly reduces the sample sizes, leaving too few observations for AA rated bonds. For A-rated bonds, the coefficients on all of our liquidity measures become statistically insignificant, albeit having the same signs as those in Table 8. For BBB-rated bonds, the coefficients of all liquidity measures remain statistically significant, and their magnitudes are also similar to those in Table 8. Results for high-yield bonds are largely unchanged. Therefore, to the extent that CDX member names have more liquid CDS contracts, we find that the nondefault component of BBB-rated bonds is clearly associated with their bond liquidity.[19]

5.3.2 Controlling for Bond Characteristics as Liquidity Proxies

We now examine the significance of our transaction-based liquidity measures after controlling for conventional liquidity proxies. The results are shown in Table 11. Comparing to our benchmark results in Table 8, the point estimates on our transaction-based liquidity measures become somewhat smaller in absolute values, but their statistical significances remain largely unchanged (except column 2). These changes are consistent with the moderate correlations we find above between the transaction-based liquidity measures and bond characteristics. Coefficients on the number of CDS quotes and lagged CDS spreads are largely unchanged. These findings suggest that our transaction-based liquidity measures identify a unique portion of the variation in the nondefault component that is orthogonal to the conventional liquidity proxies.

As for the liquidity proxies, the nondefault components are positively associated with coupon rate but uncorrelated with bond size for all rating groups. Interpreting these coefficients is difficult since both coupon rate and bond size may be correlated with the issuer's credit risk. Nondefault components are also statistically significantly related to bond age and remaining maturity. Regarding bond age, for investment-grade bonds, nondefault components are marginally lower for younger bonds; but for speculative-grade bonds nondefault components first decrease as bonds get older within four years of issuance but then increase in age. Regarding remaining maturity, for investment-grade bonds, nondefault components are higher for remaining maturity less than two years and then are roughly flat for longer maturities; but for speculative-grade bonds, nondefault components decrease more precipitously in remaining maturity. Our findings on remaining maturity are consistent with previous studies suggesting that a large fraction of investment-grade bond yield spreads, especially at the short end of the maturity range, cannot be accounted for by credit risk (e.g., Huang and Huang, 2003).

It is worth pointing out that some of our results are opposite to what have been found in the literature, for example, Longstaff *et al.* (2005) found nondefault components were found to be negatively related to bond size and positively with remaining maturity. Besides that our sample is much more representative, another possible reason for these differences may be due to our control for unobservable firm heterogeneity. In particular, previous studies may have picked up the correlation between bond characteristics and nondefault components effectively by comparing, say, large or long-term bonds issued by one firm to, respectively, small or short-term bonds issued by another firm. If credit quality and

[19] BBB-rated CDS may be generally more liquid than other contracts in part due to the greater tendency of the market participants to use them to construct synthetic CDOs. The assets in the synthetic CDOs are generally required to have investment-grade rates, and BBB-rated CDS are those meeting that requirement with the highest cash flows.

unobservable firm heterogeneity are not well controlled for, those findings may just reflect the correlation between bond size or maturity and credit risk.

5.3.3 Explicitly Controlling for Macroeconomic Conditions

While using time dummy variables may control for macroeconomic conditions, their coefficients may not be easily interpreted. To get a sense how the nondefault component is associated with macroeconomic conditions, we replace the time dummies with the following commonly-used macroeconomic variables as explicit controls: 6-month T-bill rate and term spread between 10-year Treasury rate and 6-month T-bill rate; monthly returns and implied volatilities on the S&P 500 index; and the on-the-run spread for 10-year Treasury securities. The Treasury term structure is commonly viewed as indicators for the current state of business cycle, while other variables are associated with risk premiums and liquidity in stock and Treasury markets which may affect corporate bond prices (Ericsson and Renault, 2006; de Jong and Driessen, 2006; Das and Hanouna, 2009).

The results are shown in Table 12. Comparing to Table 11, the results on our transaction-based liquidity measures are largely unchanged (with somewhat lower significance level), so are those on CDS liquidity proxies and bond characteristics (not shown). On the macroeconomic variables, nondefault components are negatively associated with short rate and term spread. Since Treasury term structures often increase on stronger outlook for economic growth, this result suggests that nondefault components decrease on better economic perspectives. This is consistent with the negative correlation between nondefault components and S&P 500 stock returns (when they are statistically significant). Finally, nondefault components are found to increase in S&P implied volatility for only high-yield bonds. Results on 10-year Treasury on-the-run premium – a proxy for Treasury market liquidity – are only positively significant for AA and A-rated bonds, as they may be closer substitutes for Treasury securities.

5.3.4 Using Liquidity Measures Estimated from “Non-News-Driven” Trades

Since transaction price, trade size, and trading frequency may be affected by both bond liquidity and valuations, changes in our transaction-based liquidity measures may also reflect changes in firm fundamentals, especially when news arrives. To mitigate the potential impact of news, we now use only transactions occurring between 10:30AM and 3:30PM each day to exclude possibly news-driven trades. We choose this time window because company news usually arrives in the after-market hours and major economic data are generally released no later than 10AM.[20]

[20] Note that restricting the trade window not only drops a set of bonds and firms from our sample but also changes the values of the liquidity measures for the bonds remaining in the sample. Thus, any changes in our regression results reflect the effects of both factors.

The results, shown in Table 13, suggest that excluding news-driven trades in general leads to more moderate liquidity effects. Comparing to Table 11, the results on A-rated bonds are roughly unchanged. But for AA- and BBB-rated bonds, most coefficients become statistically insignificant, although they continue to have the expected signs. Coefficients for speculative-grade bonds remain statistically insignificant. To the extent that bond liquidity may vary when news arrives, the above results also suggest that news helps to identify the dynamic liquidity effect on the nondefault component of yield spreads.

5.3.5 Treasury Rate as Risk Free Rate

Swap rate has been regarded as the appropriate risk free rate for studying the effects of liquidity on the nondefault component, as it offers a better control for tax effects and is arguably closer to dealers' funding cost. Nonetheless, as mentioned early, using swap rate has its own drawbacks. For example, swap rate may have a component compensating for counterparty default risks, and the benchmark LIBOR rate also has a credit risk component. For robustness, we follow the literature to repeat our regressions with the nondefault component estimated using Treasury rate as the risk free rate.

The results are shown in Table 14. Comparing to Table 11, the results are roughly unchanged for both investment-grade and speculative-grade bonds. These suggest that the difference in the estimated nondefault components resulting from using alternative risk free rates is largely uncorrelated with our transaction-based liquidity measures.

Among other regressors, notable changes occur to the coefficients on coupon rate: They become slightly smaller for investment-grade bonds but slightly larger for speculative-grade bonds. On a related note, Longstaff *et al.* (2005) argued that one can use the difference in the estimated coefficients on coupon rate between using Treasury rate and using swap rate as an estimate for the tax effect on corporate bond yield spread. Based on our estimates, this would result in a negative tax effect for investment-grade bonds but a positive tax effect for speculative-grade bonds! Our results thus suggest that their method of identifying tax effect at best may not be robust to the controlling for transaction-based liquidity effect or for unobservable firm heterogeneity. Clearly, more research questions remain regarding the tax effect.

5.3.6 No Correction for Coupon Effects

We have argued that we improve the estimation of the nondefault component of yield spreads by fully correcting coupon effect. What happens if we don't adjust for coupon effect? We reestimate our models with the nondefault component equal to bond spreads minus the CDS spread that is read directly at the comparable maturity from the CDS term structure (i.e., Line 3 in Table 2).

The results with swap rate as the risk free rate are shown in Table 15. Comparing to Table 11, the results on our liquidity measures are roughly unchanged, suggesting that the coupon effects are largely orthogonal to our transaction-based liquidity measures, although they may affect the estimated levels of the nondefault component.

Not surprisingly, failing to adjust the coupon effect has significant impacts on the coefficients on coupon rates. Indeed, for investment-grade bonds they decrease by about 0.4 on average, implying that all else equal, for each percentage of coupon rate, one would underestimate the nondefault component by 0.4 basis points if the coupon effects were not removed. The impact for speculative-grade bonds is more modest.

6. Conclusion

In this paper we estimate the nondefault component of corporate bond yield spreads and examine its relationship with bond liquidity. We construct three types of bond liquidity measures, including price impact of trades, transaction costs, and trading frequency variables, using newly available intraday transactions data. In addition, we control for the default component of bond spreads using the term structure of CDS spreads, addressing both maturity mismatch and coupon effect that may have biased existing estimations. Importantly, in doing so, our methodology allows us to have enough degrees of freedom to use fixed-effects models to control for the unobservable firm heterogeneity that may otherwise bias the regression analysis.

Using swap rate as the risk free rate, the estimated nondefault component of yield spread is in general moderate and statistically significant for only AA-, A-, and BBB-rated bonds and increasing in this order both in basis points and as a fraction of yield spreads. With Treasury rate as the risk free rate, the estimated nondefault component is statistically significant for all investment-grade bonds (i.e., those rated AAA, AA, A, and BBB) and BB-rated bonds. In basis points, the nondefault component is the largest for BBB-rated bonds; but as a fraction of yield spreads, the nondefault component is decreasing in bond rating, that is, the highest for AAA-rated bonds. In addition, the nondefault component accounts more than half of yield spreads for A- and higher-rated bonds.

We find a positive and significant relationship between the nondefault component and bond illiquidity for investment-grade bonds (i.e., those rated AA, A, and BBB) but no significant relationship for speculative-grade bonds. We demonstrate that such estimated relationship would appear weaker if the unobservable firm heterogeneity were not well controlled for. We also find that the nondefault component of bond spreads comoves with indicators for macroeconomic conditions, particularly, negatively with the Treasury term structure. In addition, controlling for conventional liquidity proxies does not affect the statistical significance of our transaction-based liquidity measures, suggesting our liquidity measures identify a unique portion of the nondefault component associated with the stochastic variation in bond liquidity. Finally, the estimated effects of our transaction-based liquidity measures are robust to a number of alternative model specifications and samplings, such as excluding news-driven trades and using Treasury rate as the risk free rate.

For future research, the strong statistical evidence of the positive relationship between the nondefault component of yield spreads and bond illiquidity suggests that it is important to incorporate liquidity factors into the bond pricing models. In addition, our results call for careful reevaluations on the effects of CDS market liquidity and tax on corporate yield spreads.

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Table 1. Sample Description

Our overall sample is constructed by merging Merrill Lynch's Corporate Bond Index Database and Markit Partner's CDS Database for the period from January 1, 2001 to April 30, 2007. We retain only senior unsecured U.S. dollar-denominated bonds issued by U.S. firms that pay fixed semi-annual coupons with remaining maturity less than 15 years. We also delete bonds that are callable, puttable, convertible, or have sink fund features. In addition, to include a reference entity, we require its CDS quotes be non-missing at 1- and 10-year maturities and non-missing at additional two of the four maturities in between (i.e., 2-, 3-, 5-, and 7-year).

We merge this overall sample with the TRACE data to obtain our regression sample. The sampling period is from July 1, 2002 to April 30, 2007. In addition, for bond transaction data, we remove trades with "data errors" as in Edwards *et al.* (2007). The figures shown in Panel B reflect the sample of the bonds with at least one non-missing trading liquidity measure for any month (without winsorizing).

Note that we conduct our analysis at the monthly frequency, where monthly values of all time-varying variables are the average of their corresponding daily values.

	A. Overall Sample		B. Regression Sample	
Bond rating	N. of bonds	N. of firms	N. of bonds	N. of firms
AAA	16	5	11	4
AA	236	23	152	20
A	555	114	381	87
BBB	472	173	242	105
BB	230	88	141	56
B	88	38	44	26
$\leq$CCC	42	18	22	12
Investment-grade	1279	315	786	216
Speculative-grade	360	144	207	94
Total	1639	459	993	310
Memo:				
Unique bonds/firms[21]	1263	328	808	242

Data sources: Merill Lynch, Markit, TRACE, and Moody's.

21 The total number of unique bonds or firms is not equal to the sum over all rating categories because a bond may appear in more than one rating group due to rating changes.

Table 2. Descriptive Statistics of Liquidity Measures

Our regression sampling is constructed as described in Table 1. We calculate trading liquidity variables for each bond on each date and then use their means over each month as their monthly values. All summary statistics here are for the resulting bond-month data. Brief definitions of key variables are the following, with details shown in the main text. Let $p^i_{j,t}$ and $Q^i_{j,t}$ be the price and the size of the j th trade of bond i on date t. Amihud measure of the j th trade is $\frac{|p^i_{j,t} - p^i_{j-1,t}|}{p^i_{j-1,t}}/Q^i_{j,t}$. Using Roll's Model (1984), estimated effective bid-ask spread is $2\sqrt{-\mathrm{Cov}(r^i_{j+1,t}, r^i_{j,t})}$ with $r^i_{j,t} = \log p^i_{j,t}/p^i_{j-1,t}$. Turnover rate is the ratio of total trading volume in a month to the amount of face value outstanding. Other variables are self-explanatory.

Bond Ratings	**All**						**AA**			**A**			**BBB**			**High-yield**		
(N. of Obs.)	(15270)						(2332)			(7615)			(2927)			(2396)		
Variables	Mean	P5	P25	P50	P75	P95	P25	P50	P75	P25	P50	P75	P25	P50	P75	P25	P50	P75
Price impact of trades:																		
1. Amihud illiq. (abs(ret)/$M)	0.55	0.00	0.14	0.34	0.65	1.61	0.18	0.32	0.56	0.15	0.33	0.65	0.08	0.32	0.66	0.11	0.42	0.78
Transaction costs:																		
2. Estimated bid-ask spread (%)	1.11	0.21	0.55	0.91	1.42	2.57	0.55	0.80	1.16	0.54	0.87	1.35	0.50	0.97	1.50	0.72	1.28	1.92
Trading frequency:																		
3. Turnover rate	0.05	0.00	0.01	0.04	0.07	0.17	0.02	0.04	0.06	0.01	0.03	0.06	0.01	0.04	0.09	0.01	0.03	0.07
Bond characteristics:																		
4. Coupon (%)	6.24	3.60	5.25	6.38	7.20	8.75	4.63	5.45	6.63	5.00	6.15	7.05	5.50	6.40	7.20	6.63	7.20	7.90
5. Age (year)	4.88	0.32	1.69	3.73	7.45	12.72	1.43	3.16	6.23	1.63	3.72	7.10	1.48	3.24	7.51	2.82	5.97	8.45
6. Term-to-maturity (year)	5.13	1.28	2.42	4.21	7.38	11.79	2.42	4.13	6.59	2.37	4.04	6.91	2.54	4.87	8.04	2.50	4.37	8.01
7. Bond size ($100mm)	6.30	1.50	2.50	4.00	8.00	20.00	3.00	8.00	13.00	2.50	4.00	7.50	2.50	3.50	7.50	1.99	2.91	5.00
Memo items:																		
8. Number of traded days	13.91	3	9	15	20	22	13	19	21	10	16	20	5	10	19	8	13	18
9. Number of trades	118.88	4	17	44	133	450	33	100	224	20	48	119	9	23	127	15	35	90
10. Median trade size ($MM)	0.20	0.01	0.02	0.03	0.08	1.00	0.03	0.03	0.05	0.02	0.03	0.05	0.02	0.04	0.26	0.02	0.04	0.35
11. Monthly trading vol ($MM)	43.83	0.33	4.01	14.82	47.22	170.70	6.09	28.00	69.52	3.93	14.13	43.72	4.06	15.68	63.46	2.92	10.21	27.90

Data sources: Merill Lynch, Markit, TRACE, Federal Reserve Board, from July 2002 to April 2007.

Table 3. Pairwise Correlations of Liquidity Measures

This table shows the pairwise correlations of transaction-based liquidity measures for each rating group. * indicates the correlation coefficient is statistically significant at the 95 percent confidence level.

Correlation	AA	A	BBB	High-yield
Corr(Amihud, Bid-ask)	0.49*	0.37*	0.36*	0.41*
Corr(Amihud, Turnover)	-0.08*	-0.06*	-0.03	-0.00
Corr(Bid-ask, Turnover)	0.00	-0.04*	0.04*	0.08*

Table 4. Relationship between Transaction Based Liquidity Measures and Liquidity Proxies

(1) Liquidity variables are defined as shown in Table 2. (2) Each column is a regression model of the form:

$$\log(\text{Bond [il]liquidity}) = \alpha + \beta \text{liq. proxies} + \text{firm and time fixed effects} + \varepsilon,$$

where [il]liquidity measure used for the corresponding model is indicated in the row under the column numbers. (3) Figures in parentheses are robust standard errors, and * and ** indicate that the coefficient is statistically significant at the 90 and the 95 percent confidence levels, respectively.

Dependent variable = log (Bond [il]liquidity measure)	AA-, AA, AA+			A-, A, A+			BBB-, BBB, BBB+			Speculative-grade		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Amihud	Bid-ask	Turnover	Amihud	Bid-ask	Turnover	Amihud	Bid-ask	Turnover	Amihud	Bid-ask	Turnover
Coupon	-0.08**	-0.04**	-0.04*	-0.06**	0.00	-0.07**	-0.04	0.01	-0.10**	-0.23**	-0.03	-0.05*
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.1)	(0.0)	(0.0)
Log(Bond size)	0.20**	-0.07**	0.28**	0.27**	-0.06**	0.36**	-0.02	-0.10**	0.24**	0.11*	-0.03	0.18**
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.1)	(0.0)	(0.1)	(0.1)	(0.0)	(0.1)
Bond age/10	2.94**	0.94**	-4.20**	2.72**	0.35**	-3.46**	4.15**	1.56**	-3.12**	5.90**	1.99**	-1.64**
	(0.4)	(0.2)	(0.4)	(0.3)	(0.2)	(0.3)	(0.8)	(0.4)	(0.6)	(1.1)	(0.5)	(0.6)
$(Bondage/10)^2$	-2.51**	-0.66	5.57**	-1.54**	0.49	4.99**	-4.36**	-2.39**	4.20**	-7.78**	-2.84**	2.19**
	(0.8)	(0.5)	(0.8)	(0.7)	(0.4)	(0.6)	(1.7)	(0.9)	(1.2)	(1.9)	(0.8)	(1.0)
$(Bondage/10)^3$	1.05**	0.11	-3.07**	0.22	-0.60**	-2.96**	2.41**	1.58**	-2.25**	4.64**	1.73**	-0.95
	(0.5)	(0.3)	(0.5)	(0.4)	(0.3)	(0.4)	(1.2)	(0.6)	(0.8)	(1.2)	(0.5)	(0.6)
$(Bondage/10)^4$	-0.19*	-0.00	0.56**	-0.01	0.13**	0.55**	-0.47**	-0.32**	0.40**	-0.94**	-0.35**	0.13
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	(0.2)	(0.2)	(0.1)	(0.1)
Term-to-maturity/10	2.91**	3.66**	-4.83**	1.90**	2.24**	-5.38**	4.98*	3.69**	-2.20	2.60	3.49**	-1.92
	(1.4)	(0.9)	(1.6)	(1.0)	(0.5)	(0.8)	(2.5)	(1.1)	(1.6)	(2.2)	(1.1)	(1.5)
$(TTM/10)^2$	-2.64	-5.57**	11.70**	2.23	-1.20	12.40**	-6.43	-4.58	6.21	-2.03	-5.32*	6.91*
	(3.8)	(2.4)	(4.4)	(2.5)	(1.4)	(2.2)	(7.2)	(3.1)	(4.3)	(6.2)	(3.1)	(3.8)
$(TTM/10)^3$	1.77	5.10**	-11.59**	-5.47**	-0.29	-11.28**	3.93	2.62	-5.86	-1.38	3.20	-6.73*
	(4.0)	(2.5)	(4.8)	(2.5)	(1.4)	(2.2)	(8.0)	(3.4)	(4.6)	(6.4)	(3.2)	(3.8)
$(TTM/10)^4$	-0.59	-1.78**	3.87**	2.38**	0.30	3.43**	-1.04	-0.59	1.66	1.31	-0.61	2.10*
	(1.4)	(0.9)	(1.8)	(0.9)	(0.5)	(0.8)	(3.0)	(1.2)	(1.6)	(2.2)	(1.1)	(1.3)
Constant	-3.24**	-0.02	-3.39**	-3.54**	-0.03	-3.63**	-1.86**	-0.15	-2.56**	-1.35**	-0.02	-3.25**
	(0.3)	(0.2)	(0.4)	(0.2)	(0.1)	(0.2)	(0.6)	(0.3)	(0.4)	(0.6)	(0.3)	(0.6)
R^2	0.22	0.36	0.25	0.13	0.27	0.19	0.12	0.21	0.10	0.09	0.11	0.12
Number of firms	20	19	19	86	82	86	99	85	102	73	68	74
N	2210	2067	2163	6812	5983	7019	2400	1837	2429	2074	1579	2186

Table 5. Cross-Sectional Default and Nondefault Components of Bond Spreads

(A) To construct the cross-sectional sample, we first remove bonds that were ever either upgraded or downgraded (in terms of changing whole rating letter) in the overall sample. We also remove bonds that appear in less than three months over the sample period. For each bond, we then compute means of the relevant variables over the sample period. For this resulting cross-sectional of bonds, we report means of bond spreads, default and nondefault components of the spreads with either Treasury or swap rate as the risk-free rate. (B) * indicates statistically significance at the 95 percent confidence level of a test of the null hypothesis that the nondefault component (in basis point in Columns (3) and (7), and in fraction in Columns in (4) and (8)) is zero.

	Swap rate				Treasury rate				
Rating	Spread	DefComp.	Nondef.	$\frac{\text{Nondef}}{\text{Spread}}$	Spread	DefComp.	Nondef.	$\frac{\text{Nondef}}{\text{Spread}}$	N
	(1)	(2)	(3)	$(4)=\frac{(3)}{(1)}$	(5)	(6)	(7)	$(8)=\frac{(7)}{(5)}$	
AAA	9.5	9.1	0.3	0.04	41.2	9.4	31.8*	0.77*	14
AA	24.5	21.2	3.3*	0.13*	62.1	21.2	40.9*	0.66*	120
A	48.4	41.7	6.7*	0.14*	86.8	41.5	45.3*	0.52*	328
BBB	108.1	84.6	23.5*	0.22*	146.1	84.3	61.8*	0.42*	281
BB	211.9	209.1	2.8	0.01	250.1	208.7	41.4*	0.17*	85
B	336.5	389.9	-53.5*	-0.16*	379.9	389.3	-9.4	-0.02	19
CCC	441.0	516.5	-75.4	-0.17	476.6	515.9	-39.3	-0.08	6
CC	1180.5	1319.6	-139.2	-0.12	1222.0	1318.9	-96.8	-0.08	1
IG	66.4	54.0	12.4*	0.19*	104.4	53.8	50.5*	0.48*	743
HY	254.3	266.7	-12.3	-0.05	293.3	266.2	27.1*	0.09*	111

Table 6. Results of OLS Regressions of Nondefault Bond Spreads on Bond Liquidity Measures with Time Fixed Effects

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{time fixed effects} + \varepsilon.$$

(3) Figures in parentheses are robust standard errors with clustering at the firm level. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

	Dependent variable = Bond yield − CDS implied yield with swap rate															
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud illiq.)	1.13**			1.36**	0.53			0.65	-0.51			-0.36	-1.01			-0.13
	(0.4)			(0.3)	(0.4)			(0.4)	(1.0)			(1.0)	(0.7)			(0.9)
Log(Bid-ask spreads)		2.39*		1.11		1.94**		1.01*		-3.19		-3.56		-1.80		-1.38
		(1.3)		(1.3)		(0.8)		(0.6)		(3.1)		(2.2)		(2.4)		(2.5)
Log(Turnover rate)			-1.61**	-1.38**			-1.30**	-1.11*			-3.61**	-5.39**			-1.85	-4.24**
			(0.6)	(0.5)			(0.5)	(0.6)			(1.7)	(2.1)			(2.2)	(1.6)
Constant	-2.41	-3.60	-7.02*	-6.19*	-17.9	-20.3*	-15.4	-21.8*	-9.85	-9.54	-18.3*	-24.5**	-29.2**	-53.3**	-24.8**	-61.3**
	(3.3)	(3.0)	(3.7)	(3.0)	(12)	(11)	(13)	(13)	(9.6)	(9.2)	(10)	(12)	(0.1)	(2.6)	(6.8)	(5.8)
R^2	0.10	0.11	0.13	0.14	0.14	0.15	0.13	0.16	0.26	0.29	0.28	0.36	0.06	0.08	0.05	0.10
Observations	2185	2050	2138	1914	6497	5751	6689	5182	2135	1603	2214	1320	1266	916	1366	824

Table 7. Results of OLS Regressions of Nondefault Bond Spreads on Bond Liquidity Measures with Both Firm and Time Fixed Effects

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{firm and time fixed effects} + \varepsilon.$$

(3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with swap rate																
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud illiq.)	0.79**			0.74**	0.76**			0.65**	0.11			-0.16	-0.96**			-0.63
	(0.2)			(0.3)	(0.1)			(0.2)	(0.2)			(0.4)	(0.4)			(0.7)
Log(Bid-ask spreads)		1.80**		0.96**		1.74**		0.89**		-0.98*		-2.31**		-5.17**		-4.31**
		(0.4)		(0.5)		(0.3)		(0.3)		(0.6)		(0.7)		(1.2)		(1.6)
Log(Turnover rate)			-1.37**	-1.28**			-1.09**	-0.90**			-1.38**	-1.98**			-3.34**	-4.07**
			(0.2)	(0.3)			(0.2)	(0.2)			(0.3)	(0.4)			(0.7)	(1.1)
Constant	-3.28	-4.48	-7.59*	-7.89*	-3.60	-7.47*	-2.45	-6.36*	-3.46	-6.63**	-3.33	-9.98**	-12.3	6.83	-37.8**	-13.6**
	(3.8)	(3.6)	(4.2)	(4.3)	(3.6)	(3.9)	(3.4)	(3.7)	(2.7)	(2.7)	(3.3)	(2.7)	(20)	(4.2)	(8.2)	(6.7)
R^2	0.11	0.11	0.13	0.14	0.13	0.13	0.13	0.15	0.10	0.10	0.12	0.12	0.06	0.09	0.07	0.11
Number of firms	20	19	19	18	82	77	81	75	95	83	99	75	61	59	66	58
Observations	2185	2050	2138	1914	6497	5751	6689	5182	2135	1603	2214	1320	1266	916	1366	824

Table 8. The Effects of Bond Liquidity on the Nondefault Bond Spreads by Controlling for CDS Liquidity

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{CDS liquidity proxies} + \text{firm and time fixed effects} + \varepsilon.$$

(3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with swap rate																
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud Illiq.)	0.45*			0.50	0.76**			0.57**	0.74**			0.62*	-0.11			-0.05
	(0.3)			(0.3)	(0.1)			(0.2)	(0.2)			(0.4)	(0.3)			(0.6)
Log(Bid-ask spread)		1.35**		0.60		2.00**		1.13**		1.73**		-0.11		0.06		0.74
		(0.5)		(0.6)		(0.3)		(0.3)		(0.5)		(0.6)		(1.2)		(1.5)
Log(Turnover rate)			-1.39**	-1.29**			-1.12**	-0.85**			-1.26**	-1.41**			0.19	0.37
			(0.2)	(0.2)			(0.2)	(0.2)			(0.3)	(0.4)			(0.7)	(1.1)
N. of CDS quotes	-0.15	-0.16	-0.04	-0.11	0.42**	0.37**	0.42**	0.41**	0.11	0.44**	0.12	0.69**	0.33	0.22	0.53*	0.44
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	(0.2)	(0.3)	(0.4)	(0.3)	(0.4)
Lagged CDS spread	0.08**	0.07**	0.09**	0.08**	-0.04**	-0.04**	-0.02*	-0.03**	-0.17**	-0.18**	-0.16**	-0.17**	-0.13**	-0.12**	-0.14**	-0.13**
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Constant	-4.35	-4.79	-12.36**	-3.12	10.58**	9.36**	-14.63**	-16.32**	27.74**	25.22**	24.54**	23.38**	-13.10*	80.71**	62.06**	56.58**
	(4.6)	(5.8)	(4.5)	(5.3)	(4.7)	(4.4)	(3.6)	(3.9)	(2.1)	(2.7)	(2.0)	(2.8)	(7.2)	(15.3)	(12.6)	(17.8)
R^2	0.12	0.13	0.14	0.15	0.15	0.15	0.15	0.17	0.25	0.27	0.25	0.28	0.31	0.29	0.31	0.32
Number of firms	19	18	18	18	77	76	77	73	86	77	87	70	58	56	61	55
N	1991	1872	1956	1762	6137	5458	6340	4959	1994	1513	2061	1267	1172	848	1262	770

Table 9. Economic Magnitude of the Effect of Bond Liquidity on the Nondefault Bond Spreads

This table presents the magnitude of the effects, both actual values and as fractions of bond spreads, of bond liquidity on the nondefault component of bond spread based on results in Table 8. The effects are computed as the change in the nondefault bond spread when the liquidity measure increases from its 25th percentile to its 75th percentile. Only those with statistically significant coefficients are shown. Figures in the brackets represent the 95 percent confidence intervals of the estimates.

	Changes in nondefault component			Changes as percent of total spreads		
	AA	A	BBB	AA	A	BBB
1. Amihud illiquidity	0.51	1.11	1.56	2.0	2.3	1.4
	[-0.15, 1.17]	[0.83, 1.40]	[0.74, 2.38]	[-0.6, 4.7]	[1.7, 2.9]	[0.7, 2.2]
2. Bid-ask spread	1.01	1.83	1.90	4.0	3.8	1.8
	[0.28, 1.74]	[1.30, 2.37]	[0.83, 2.97]	[1.1, 6.9]	[2.7, 4,9]	[0.8, 2.8]
3. Turnover rate	-1.53	-2.01	-2.77	-6.1	-4.2	-2.6
	[-1.96, -1.10]	[-2.71, -1.31]	[-4.05, -1.48]	[-7.8, -4.4]	[-5.6, -2.7]	[-3.8, -1.4]
Memo. Median in basis points for overall samples:						
4. Yield spread [a]	25	48	108			
5. Nondefault comp. [b]	3.3	6.7	23.5			

[a] Yield spread = bond yield − swap rate.

[b] Nondefault comp. = bond yield − CDS implied yield with swap rate as risk-free rate.

Table 10. Estimating Liquidity Effects on Nondefault Component Spreads with CDX Members Only

This table shows estimation results using only the bonds issued by firms that are members of the CDX indexes. For this subset of firms, there are insufficient numbers of bonds rated AA- or higher. Thus we don't have results for AA sample. As in the main text, each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{CDS liquidity proxies} + \text{firm and time fixed effects} + \varepsilon.$$

Figures in parentheses are robust standard errors; and * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with swap rate												
	A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Amihud Illiq.)	0.28			0.06	0.74**			0.78	0.00			0.32
	(0.3)			(0.3)	(0.3)			(0.6)	(0.4)			(0.8)
Log(Bid-ask spread)		0.26		-0.19		1.77**		-0.56		0.09		0.69
		(0.5)		(0.5)		(0.7)		(0.8)		(1.4)		(1.9)
Log(Turnover rate)			-0.32	-0.11			-1.24**	-0.91*			0.34	1.43
			(0.3)	(0.3)			(0.4)	(0.5)			(0.9)	(1.4)
N. of CDS quotes	0.09	-0.09	0.03	0.07	0.67**	0.87**	0.80**	1.03**	0.12	-0.19	0.46	-0.00
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.4)	(0.4)	(0.3)	(0.5)
Lagged CDS spread	-0.04**	-0.03	-0.05**	-0.03	-0.18**	-0.16**	-0.18**	-0.15**	-0.13**	-0.11**	-0.13**	-0.12**
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Constant	3.70	5.92*	1.61	3.19	2.69	-5.11	12.95**	0.63	19.47**	51.19**	16.56**	36.93**
	(3.6)	(3.3)	(2.6)	(2.8)	(4.3)	(4.4)	(5.3)	(5.0)	(4.5)	(4.9)	(7.1)	(9.3)
R^2	0.22	0.21	0.20	0.24	0.22	0.23	0.24	0.23	0.31	0.28	0.30	0.28
Number of firms	21	21	20	20	41	37	41	35	38	38	38	38
N	1576	1508	1632	1358	1029	802	1005	661	837	594	875	534

Table 11. Estimating Liquidity Effects with Both Transaction Based Liquidity Measures and Liquidity Proxies

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{bond characteristics} + \text{CDS liquidity proxies} + \text{firm and time fixed effects} + \varepsilon.$$

(3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with swap rate																
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud Illiq.)	0.00			0.08	0.42**			0.19	0.46**			0.14	-0.30			-0.30
	(0.2)			(0.3)	(0.1)			(0.2)	(0.2)			(0.3)	(0.4)			(0.6)
Log(Bid-ask spread)		0.71		0.40		1.15**		0.86**		1.32**		0.56		0.03		1.20
		(0.5)		(0.5)		(0.3)		(0.3)		(0.5)		(0.6)		(1.2)		(1.4)
Log(Turnover rate)			-0.71**	-0.54**			-0.40**	-0.27			-0.57**	-0.63			1.07	1.14
			(0.2)	(0.3)			(0.2)	(0.2)			(0.3)	(0.4)			(0.7)	(1.1)
N. of CDS quotes	-0.17**	-0.21**	-0.05	-0.17*	0.38**	0.37**	0.38**	0.37**	0.15	0.50**	0.18	0.71**	0.42	0.38	0.57**	0.60
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	(0.2)	(0.3)	(0.4)	(0.3)	(0.4)
Lagged CDS spread	-0.07	-0.07	-0.10	-0.08	-0.07**	-0.06**	-0.05**	-0.06**	-0.15**	-0.16**	-0.14**	-0.16**	-0.10**	-0.09**	-0.12**	-0.11**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Coupon	1.19**	1.05**	1.07**	0.92**	2.08**	1.93**	1.96**	1.93**	2.30**	2.64**	2.22**	2.15**	4.66**	5.05**	4.22**	4.95**
	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.5)	(0.5)	(0.5)	(0.6)	(1.0)	(1.3)	(1.0)	(1.3)
Log(Bond size)	-0.67*	-0.52	-0.36	-0.29	-0.21	-0.00	-0.07	0.16	-0.65	-0.61	-0.02	0.41	-4.68**	-3.98	-4.25**	-4.62*
	(0.3)	(0.4)	(0.3)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)	(1.0)	(1.1)	(1.0)	(1.1)	(2.0)	(2.5)	(1.9)	(2.5)
Constant	10.97**	11.82**	6.86	11.37*	20.00**	15.26**	-4.50	-8.12*	47.07**	46.63**	41.86**	44.17**	-7.82	69.81**	-18.93	55.44**
	(4.9)	(5.5)	(4.7)	(6.6)	(5.3)	(5.2)	(4.4)	(4.9)	(9.3)	(10.8)	(9.3)	(12.1)	(15.3)	(23.8)	(13.7)	(25.3)
Bond age polyn. (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TTM polyn. (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.29	0.31	0.30	0.32	0.26	0.25	0.25	0.26	0.37	0.41	0.37	0.41	0.38	0.36	0.37	0.39
Number of firms	19	18	18	18	77	76	77	73	86	77	87	70	58	56	61	55
N	1991	1872	1956	1762	6137	5458	6340	4959	1994	1513	2061	1267	1172	848	1262	770

Table 12. The Effects of Liquidity on Nondefault Bond Spreads When Explicitly Controlling for Macroeconomic Conditions

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Basis spread} = c + \alpha \log(\text{Bond [il]liquidity measures}) + \beta \text{bond char.} + \gamma \text{CDS liq. proxies} + \theta \text{macro variables} + \text{firm fixed effects} + \varepsilon.$$

(3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with swap rate																
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud Illiq.)	-0.03			0.01	0.50**			0.25	0.34*			0.10	-0.39			-0.15
	(0.2)			(0.3)	(0.1)			(0.2)	(0.2)			(0.4)	(0.4)			(0.6)
Log(Bid-ask spread)		0.77*		0.52		1.25**		0.92**		1.43**		0.83		-0.92		0.37
		(0.4)		(0.5)		(0.3)		(0.3)		(0.5)		(0.6)		(1.2)		(1.3)
Log(Turnover rate)			-0.61**	-0.43*			-0.32*	-0.21			-0.38	-0.23			1.33*	1.95*
			(0.2)	(0.3)			(0.2)	(0.2)			(0.3)	(0.4)			(0.7)	(1.1)
6-Month T-bill	-4.50**	-4.31**	-4.86**	-4.52**	-5.63**	-5.77**	-5.57**	-5.61**	-6.44**	-5.07**	-6.28**	-5.40**	-6.93**	-4.95	-3.94	-1.62
	(0.8)	(0.8)	(0.8)	(0.8)	(0.5)	(0.5)	(0.5)	(0.5)	(1.1)	(1.2)	(1.0)	(1.3)	(3.0)	(3.8)	(2.9)	(3.9)
Treas term spread	-6.57**	-6.63**	-7.11**	-6.83**	-8.12**	-8.26**	-8.23**	-8.34**	-7.73**	-6.11**	-6.95**	-6.49**	-8.84**	-5.84	-4.05	-2.49
	(0.9)	(1.0)	(1.0)	(1.0)	(0.6)	(0.7)	(0.6)	(0.7)	(1.4)	(1.5)	(1.3)	(1.6)	(4.0)	(5.0)	(3.8)	(4.9)
S&P 500 return	5.68*	4.98	7.42**	6.39*	-7.28**	-8.54**	-4.77**	-7.76**	-0.32	-1.75	-2.55	-6.54	-6.57	-4.01	8.57	31.18
	(3.1)	(3.3)	(3.2)	(3.4)	(2.3)	(2.5)	(2.3)	(2.5)	(5.5)	(5.8)	(5.4)	(6.2)	(22.2)	(30.8)	(23.5)	(29.6)
S&P impl. vol.	0.07	0.03	0.14	0.06	0.01	-0.12	0.04	-0.03	0.10	0.30	-0.02	0.26	0.98**	0.40	-0.10	0.18
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)	(0.5)	(0.5)	(0.4)	(0.5)
Treas. liquidity	0.28**	0.29**	0.32**	0.33**	0.27**	0.24**	0.26**	0.28**	0.30	0.29	0.24	0.30	-0.27	-0.35	-0.95**	-0.37
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)	(0.4)	(0.5)	(0.4)	(0.5)
Constant	39.96**	41.63**	37.42**	39.05**	43.79**	44.66**	40.43**	42.51**	67.98**	61.28**	63.34**	53.90**	42.70**	28.59	35.51*	25.80
	(4.9)	(5.1)	(4.8)	(5.4)	(4.1)	(4.3)	(4.0)	(4.5)	(10.9)	(12.7)	(10.4)	(13.7)	(19.3)	(24.8)	(18.6)	(26.7)
Bond char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CDS liq. proxies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.23	0.25	0.24	0.25	0.17	0.17	0.16	0.18	0.26	0.27	0.25	0.26	0.26	0.27	0.29	0.30
Number of firms	19	18	18	18	77	76	77	73	86	77	87	70	58	56	61	55
N	1991	1872	1956	1762	6137	5458	6340	4959	1994	1513	2061	1267	1172	848	1262	770

Table 13. The Effects of Liquidity on Nondefault Bond Spreads When Liquidity Measures Are Computed Using "Non-News" Driven Trades

This table shows regression results with our liquidity measures computed using only trades outside major news hours. (1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{bond characteristics} + \text{CDS liquidity proxies} + \text{firm and time fixed effects} + \varepsilon,$$

where bond liquidity measures are computed using only transactions occurred between 10:30AM and 3:30PM on any trading days. (3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with swap rate																
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud illiq.)	0.00			-0.13	0.31**			0.10	0.23			0.26	-0.06			-0.34
	(0.21)			(0.28)	(0.13)			(0.20)	(0.17)			(0.37)	(0.32)			(0.69)
Log(Bid-ask spreads)		0.18		-0.04		1.24**		1.10**		0.44		-0.18		-0.12		0.49
		(0.37)		(0.40)		(0.28)		(0.32)		(0.58)		(0.68)		(1.14)		(1.29)
Log(Turnover rate)			-0.26	-0.41			-0.42**	-0.26			-0.41*	-0.61			0.91	1.31
			(0.22)	(0.26)			(0.14)	(0.19)			(0.22)	(0.38)			(0.63)	(1.13)
Bond char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CDS liq. proxies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1964	1771	1955	1682	5947	4837	6229	4406	1860	1259	1985	1066	1033	638	1135	585
Number of firms	18	17	18	17	77	74	77	72	84	69	85	62	57	52	59	51
R^2	0.29	0.32	0.29	0.32	0.25	0.26	0.24	0.27	0.37	0.41	0.38	0.41	0.36	0.38	0.34	0.38

Table 14. The Effects of Liquidity on Nondefault Bond Spreads When Treasury Rate Is Used as Risk-Free Rate

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{bond characteristics} + \text{CDS liquidity proxies} + \text{firm and time fixed effects} + \varepsilon,$$

where CDS implied bond yields are computed using Treasury rate as risk-free rate. (3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − CDS implied yield with Treasury rate																
		AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade		
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud illiq.)	-0.13			-0.20	0.51**			0.31	0.38*			0.19	-0.46			-0.52
	(0.27)			(0.33)	(0.15)			(0.22)	(0.20)			(0.35)	(0.39)			(0.65)
Log(Bid-ask spreads)		0.76		0.69		1.07**		0.68*		0.69		-0.25		-0.01		1.05
		(0.50)		(0.54)		(0.31)		(0.35)		(0.51)		(0.62)		(1.15)		(1.44)
Log(Turnover rate)			-0.93**	-0.71**			-0.37**	-0.23			-0.51**	-0.54			0.51	0.81
			(0.27)	(0.29)			(0.18)	(0.21)			(0.25)	(0.39)			(0.79)	(1.23)
Coupon	0.95**	0.90**	0.93**	0.79**	1.93**	1.76**	1.85**	1.72**	2.01**	2.47**	2.01**	2.01**	5.04**	5.53**	4.32**	5.72**
	(0.28)	(0.29)	(0.29)	(0.30)	(0.17)	(0.18)	(0.17)	(0.18)	(0.47)	(0.50)	(0.46)	(0.59)	(1.07)	(1.30)	(0.97)	(1.43)
Bond char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CDS liq. proxies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1986	1868	1949	1759	6173	5487	6389	4982	1891	1412	1955	1174	1003	722	1078	652
Number of firms	19	18	18	18	79	77	79	74	87	76	88	69	57	52	59	52
R^2	0.46	0.49	0.48	0.50	0.32	0.32	0.31	0.33	0.35	0.37	0.33	0.35	0.35	0.37	0.33	0.37

Table 15. The Effects of Liquidity on Nondefault Bond Spreads When Coupon Effects Are Not Removed

(1) Brief variable definitions are in Table 2 with details shown in the main text. (2) Each column reports the result of the following regression:

$$\text{Nondefault spreads} = c + \alpha \log(\text{bond [il]liquidity measures}) + \text{bond characteristics} + \text{CDS liquidity proxies} + \text{firm and time fixed effects} + \varepsilon,$$

where basis spreads equal to the difference between bond spreads and comparable-maturity CDS premiums. (3) Figures in parentheses are robust standard errors. (4) * and ** indicate that the coefficient is statistically significant at the 90 and 95 percent confidence levels, respectively.

Dependent variable = Bond yield − Swap rate − CDS premium																
	AA-, AA, AA+				A-, A, A+				BBB-, BBB, BBB+				Speculative-grade			
Independent var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log(Amihud Illiquidity)	0.06			0.17	0.45**			0.12	0.40**			0.21	-0.34			-0.28
	(0.24)			(0.29)	(0.14)			(0.19)	(0.20)			(0.34)	(0.36)			(0.62)
Log(Bid-ask spreads)		1.01**		0.62		1.35**		1.13**		0.95*		0.14		-0.23		0.76
		(0.44)		(0.49)		(0.27)		(0.32)		(0.50)		(0.59)		(1.19)		(1.37)
Log(Turnover rate)			-0.80**	-0.63**			-0.34**	-0.25			-0.55**	-0.82**			0.68	0.38
			(0.23)	(0.25)			(0.16)	(0.19)			(0.25)	(0.38)			(0.74)	(1.06)
Coupon	0.79**	0.72**	0.70**	0.59**	1.62**	1.47**	1.56**	1.48**	2.04**	2.33**	1.90**	1.86**	3.80**	4.50**	3.24**	4.80**
	(0.25)	(0.25)	(0.25)	(0.27)	(0.16)	(0.16)	(0.16)	(0.17)	(0.48)	(0.52)	(0.47)	(0.60)	(1.01)	(1.27)	(0.92)	(1.38)
Bond char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CDS liq. proxies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1984	1865	1947	1757	6106	5426	6303	4931	1914	1446	1976	1203	1021	729	1103	658
Number of firms	19	18	18	18	77	76	77	73	85	75	86	68	56	52	59	51
R^2	0.27	0.29	0.28	0.31	0.25	0.25	0.24	0.26	0.36	0.39	0.36	0.40	0.37	0.37	0.35	0.37

Figure 1. Cross-Sectional Distribution of Nondefault Components of Corporate Bonds

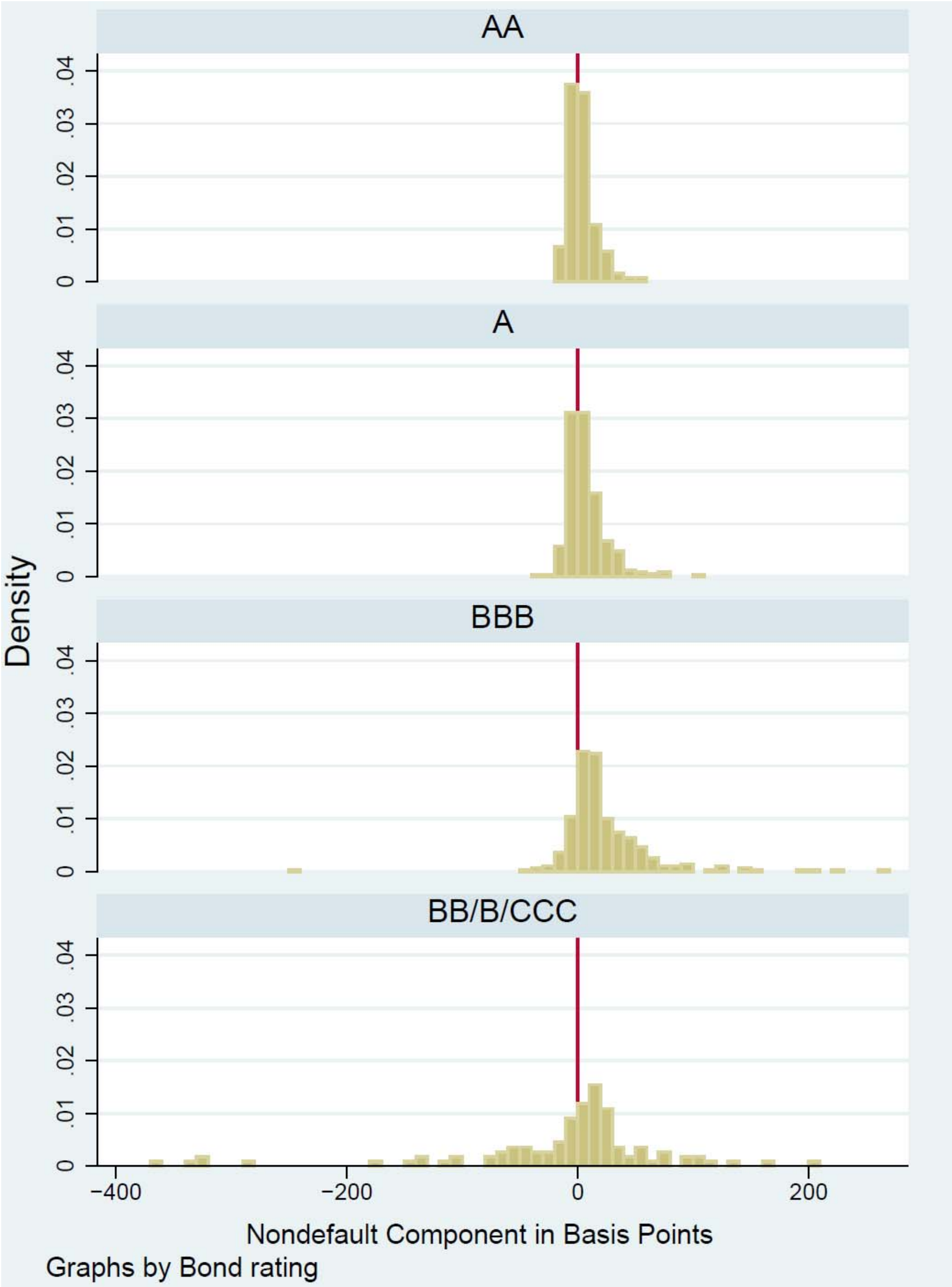
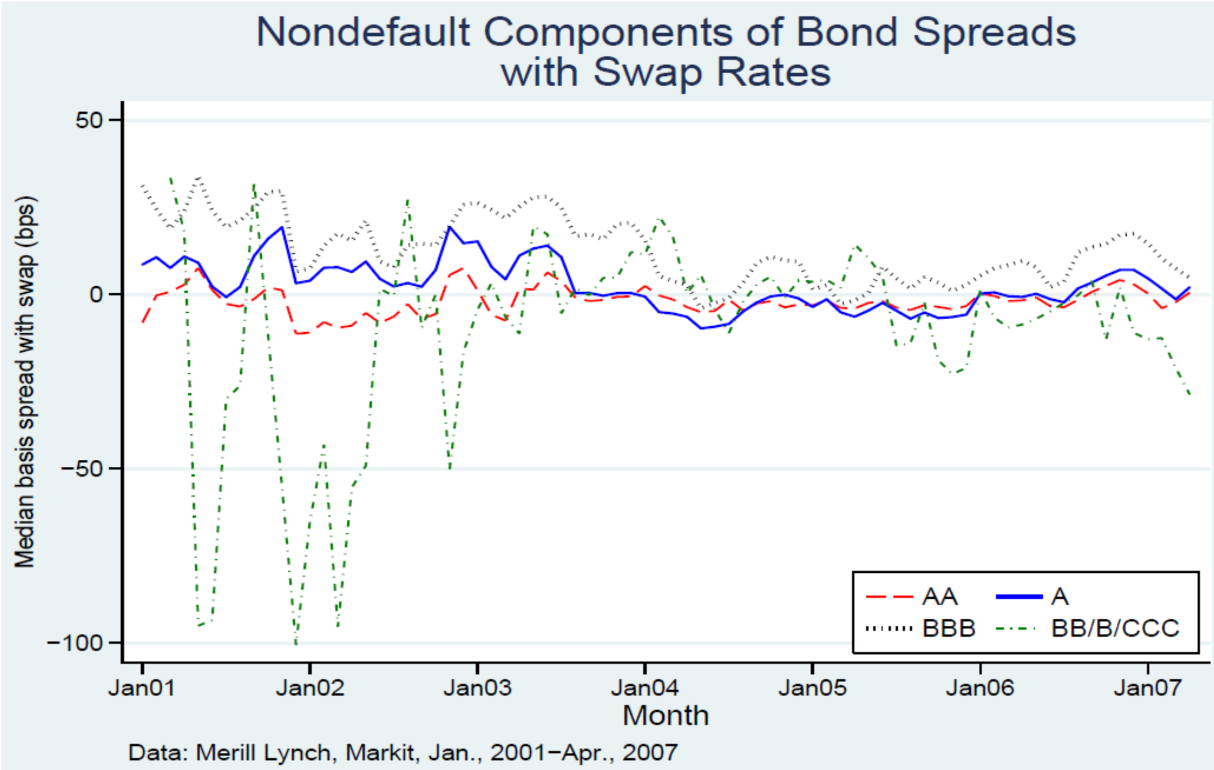
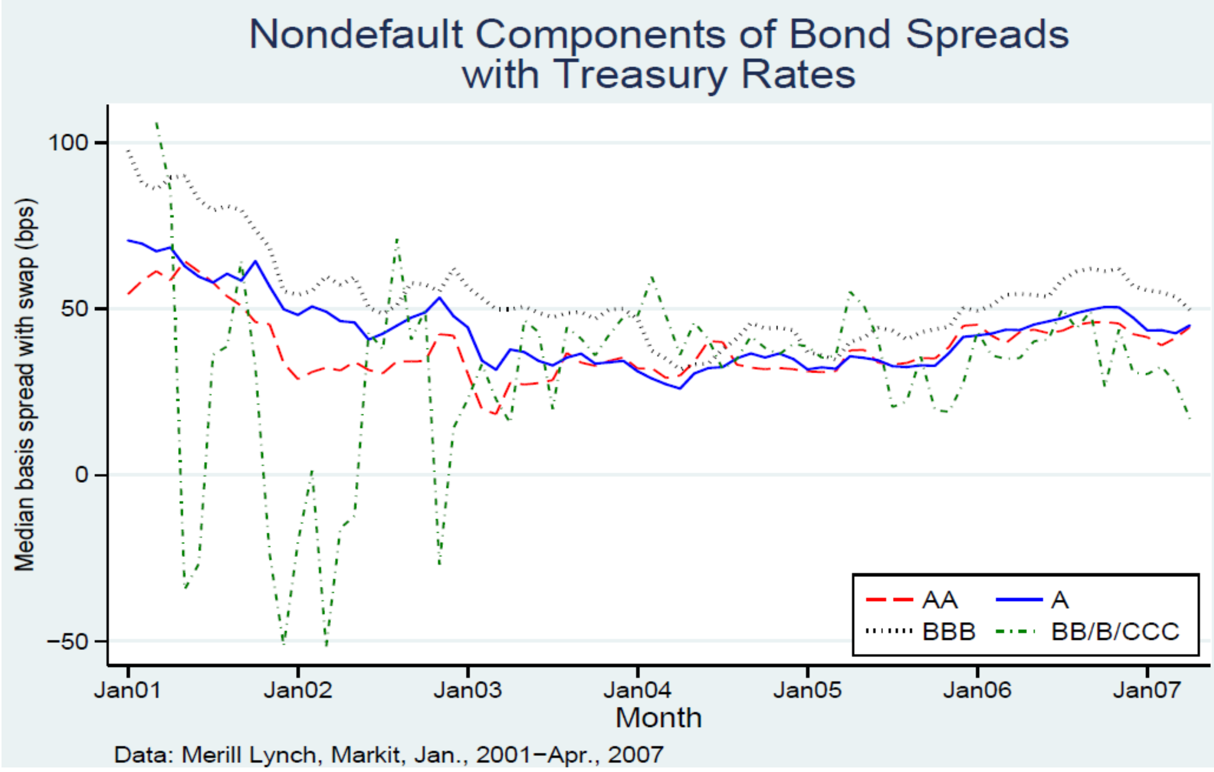


Figure 2. Time Series of Nondefault Components of Corporate Bond Spreads





Appendix 1. TRACE: The Corporate Bond Transactions Data

We construct corporate bond liquidity measures using the intraday transactions data from the NASD's Trading Reporting and Compliance Engine, or TRACE, reporting system. Under the pressure from both regulators and investors to increase the transparency of the corporate bond market, the NASD now requires its members to report to the NASD through TRACE all over-the-counter secondary market transactions for a list of eligible fixed income securities. The NASD updates the eligible list daily before the market opens. Specifically, the NASD adopted three phases to incrementally disseminate these trade reports to the public.

- Phase I: July 1, 2002, only about 500 bonds were subject to dissemination to the public. These included all investment-grade bonds with an original issue size of $1 billion or more and the 50 high-yield bonds that were rolled over from the Fixed Income Pricing System (FIPS). While small in number, these bonds reportedly accounted for about 50 percent of total trading volume at the time.

- Phase II: March 3, 2003, the NASD disseminated all investment-grade bonds with original issue size of $100 million or more and rating A3/A- or higher. Subsequently, an additional 120 BBB-rated bonds (40 each for BBB-, BBB, BBB+) were added on April 14, 2003. Total number of bonds subjected to dissemination reached about 5000 in this phase.

- Phase III: two stages leading to complete dissemination. On October 1, 2004, about 17,000 bonds were added to the dissemination list, bringing the total number of disseminated bonds to about 21,600. Later on February 7, 2005, all bonds, except the TRACE-eligible Rule 144A bonds which account for about one-sixth of all eligible bonds, became subject to dissemination, bringing the total number of disseminated bonds to about 29,300.[22]

More details on TRACE rules can be found in NASD (2004). We obtain the publicly disseminated intraday transactions data through MarketAccess. The data include bond CUSIP, NASD composite ratings, transaction price (including the effect of any dealer commission), trade size, settlement time, and other trade related variables. Our data, however, do not have some critical transaction information such as whether the trade was initiated by the buyer or the seller. An additional limitation is that the trade size available in our data is capped at $1 million for high-yield bonds and $5 million for investment-grade bonds for those trades with quantities greater than these limits.

[22] Rule 144A bonds are offered under the SEC Rule 144A. These bonds are not registered with the SEC and can only be traded among qualified institutional buyers.