Effects of Liquidity on the Non-Default 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 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 macroeconomic conditions—negatively with the Treasury term structure and positively with the stock market implied volatility.

JEL Classifications: G12, G13, G14
Key words: Corporate bond yield spreads, credit default swaps, liquidity

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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 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 macroeconomic conditions—negatively with the Treasury term structure and positively with the stock market implied volatility.

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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 estimates based on bond pricing models fit to historical data on corproate bond defaults and found mixed results (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)). 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)). A CDS is like 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, such as embedded options, that may affect the bond price, 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. Utilizing a dataset far richer than those in existing studies, our comprehensive analysis contributes to the literature in three dimensions. First, we develop a new method to estimate the default component by deriving a firm-specific discount rate curve from the term structure of its CDS spreads. We use the discount rate curve to price each of the firm's senior unsecured straight bonds and compute the implied yield as our estimate for the default component of the observed yield. Because the CDS-implied yield and the observed yield are based on identical cash flow, we are able to match exactly each bond's maturity and fully correct the coupon effect. In contrast, most existing studies used only 5-year CDS spreads and thus had to estimate a hypothetical 5-year bond yield using certain "bracket" methods. As a result, liquidity and bond characteristics, such as bond age and cash flow, of this hypothetical bond are not directly observable, limiting the scope of cross-sectional analysis and the ability to correct the coupon effect.[1]

Second, we improve the analysis of the effect of liquidity on the nondefault component of yield spreads by using 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.[2] 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).[3] Interpreting the relation between bond spreads and these proxies may be complicated by the possible correlations between the proxies

[1]Due to these difficulties, Longstaff et al. (2005) conducted their cross-sectional analysis on the bonds in the bracket instead of the 5-year hypothetical bond. The default components for those bonds are estimated using a reduced form CDS pricing model that is parametrized to fit only the 5-year CDS spreads. They also attempted to reduce the coupon effect by pricing the cash flow of the bonds in the bracket using a risk free discount rate curve. Nashikkar and Subrahmanyam (2006) used a similar strategy. Ericsson et al. (2007) fit identical models to both bond price and CDS spreads with a range of maturities and found the pricing residuals don't link to liquidity proxies.

[2]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 but 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).

[3]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.

and the issuer's credit risk. More importantly, 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.

Third, our methodology allows us to better control for the unobservable firm heterogeneity that may have biased previous estimates. The nondefault component of yield spreads may be affected by firm-specific factors, such as clientele effects, that are correlated with our liquidity measures. To the extent that these factors are unobservable, an omitted variable bias occurs in the regression estimation. Since our estimation method allows for multiple bonds by each firm at any time, we have enough degrees of freedom to apply a fixed-effects approach to control for the cross-firm variation attributable to the unobservable firm characteristics (Chen et al., 2007).

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 negative but statistically 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 particularly 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).

In our regression analysis, we link the 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.[4] 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 10 percent of total yield spreads for AA-rated bonds, 7 percent for A-rated bonds, and 4 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.[5]

We also find that the nondefault component of bond spreads comoves with macroeconomic conditions—negatively with the Treasury term structure and positively with the stock market implied volatility (VIX). This result is consistent with previous studies suggesting that corporate yield spreads are associated with marketwide liquidity factors (Collin-Dufresne et al., 2001; Duffie and Singleton, 1997; Delianedis and Geske, 2001; Liu, Longstaff and Mandell, 2006; Longstaff, 2004). 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 specifica-

[4] 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 between yield spreads and illiquidity (e.g., Fisher (1959), Perraudin and Taylor (2003), Houweling et al. (2005), and Chen et al. (2007)).

[5] 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 March (2005), and Zhu (2006)).

tions and data samplings, such as exclusing 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 presents our methodology estimating the nondefault component of yield spreads and examines its cross-sectional and time-series properties; Section 4 reports our regression results on the effects of liquidity on the nondefault component; and Section 5 concludes.

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").[6] 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.[7] We retain only senior unsecured U.S. dollar-denominated bonds issued by U.S.

[6]The yields are based on bid-side price quotes collected from dealers at 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 to add new bonds meeting a set of criteria and to remove those becoming ineligible. Among these criteria, a bond has to have a remaining maturity greater than one year throughout the incoming month and have face values outstanding larger than certain limits. Merrill's composite bond ratings may only change at the monthly rebalancing.

[7]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

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.[8]

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.[9] 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 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, somewhat more than the proportion in the overall corporate bond universe. 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 in 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 A for more details on the TRACE data). The data contain trading information such

searched on Bloomberg to complement.

[8]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.

[9]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.

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)).[10]

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 in rating, from close to 2 for B-rated bonds to about 7 for AA-rated bonds.

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 Marsh (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 taxation benefits.[11]

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.

[10] 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.

[11] 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.

We use the following conventional variables to measure macroeconomic conditions: the level and the slope of Treasury term structure, the return, historical 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 The Nondefault Component of Yield Spreads

In this section, we first describe, with an example, 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.

3.1 Estimation Method

Obviously, 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 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 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 Marsh (2005); Zhu (2006);

and Nashikkar and Subrahmanyam (2006)). 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 (see footnote 1).

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.[12] 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.[13] Under certain conditions laid out in Duffie (1999) and assuming swap rate is the appropriate measure of risk free rate, the resulting curve equals to 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.[14]

Second, from a firm's CDS-implied par yield curve, we compute zero yield curve and discount

[12]Other factors such as counterparty credit risk in CDS may also result in biased estimates of the default component of bond spread. 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. Assessing the effects of counterparty credit quantitatively is important especially in light of current financial turmoil, and we leave this for future research.

[13]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.

[14]Longstaff et al. (2005) used a reduced-form CDS pricing model to reduce the approximation errors, echoing 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)).

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". Importantly, the actual bond yield and the CDS-implied yield have identical cash flows, so we remove both maturity mismatch and coupon effect. 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 final sample. As discussed later, 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.

Our estimate for the nondefault component of yield spreads is simply the difference between the actual bond yield and the CDS-implied yield, and the default component of yield spreads is simply the difference between yield spread and the nondefault component.

In Figure 1, we show an example of our estimation for Coca-Cola Inc.. On April 30, 2007, the firm has 7 A-rated bonds outstanding, with their remaining maturities ranging from 2.4 years to 14.8 years. Quotes on CDS spreads are available at maturities from 6 month to 15 years. As shown in the top panel, our first step is to add up CDS spread and swap rate, marked as "O", and use PCHIP algorithm to fit the CDS-implied par yield curve, the solid line. Typical during this period, Coca-Cola's CDS-implied par yield curve is inverted at the short end of its maturity range. From this par yield curve, we use the standard bootstrap method to derive a zero yield curve, the dash-dotted line in the top panel, and then compute the corresponding discount rate curve, shown in the middle panel. Finally, we use this discount rate curve to price each of Coca-Cola's bonds and compute their corresponding CDS-implied yields. In the bottom panel, we contrast these CDS-implied yields, marked as "O", to the actual yields, marked as "X". Clearly, the nondefault components of yield spreads, as measured by the difference between "X" and "O" marks, vary across bonds. Below we examine the statistical properties of such variation with better controlled samples in both cross-section and time-series.

3.2 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.[15] 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 2 reports average values of yield spread and its components by bond rating. 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 investment-grade bonds except AAA-rated ones, with their sizes increasing with worse rating. In term of economic maganitude, the nondefault component is moderate in general, ranging 3 basis points and 13 percent of yield spreads for AA-rated bonds to 24 basis points and 22 percent of yield spreads for BBB-rated bonds.[16] 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 speculative-grade categories except B-rated 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

[15] 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.

[16] One possible reason that BBB-rated bonds have the lowest nondefault components may be due to the tendency of the market participants to use BBB-rated CDS 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. While we cannot explicitly control this effect, we include controls for CDS liquidity in our regression analysis.

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 2 plots by bond rating the histograms of the average nondefault component for each bond in the cross-sectional sample 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. Previous studies suggest that the variation in bond liquidity attribute to these cross-sectional variation in the nondefault component, a hypothesis we will test in the next section.

3.3 Time-Series Characteristics

Figure 3 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 3, 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.

One of our goals in the following analysis is to understand to what extent the observed time-series variation in the nondefault component are attributable to the stochastic variation in bond liquidity.

4 Effects of Liquidity on the Nondefault Component of Yield Spreads

In this section, we first describe the construction of our liquidity measures using corporate bond intraday transactions data. Then we report the regression results on the effects of liquidity on the nondefault component of yield spreads. We find a statistically significant positive relationship between the nondefault component and bond illiquidity for investment-grade bonds. Our analysis

[17]Time series plots of the mean values of the monthly nondefault component are resemble 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.

also suggests that our liquidity measures identify a unique portion of the time variation in the nondefault component and that the nondefault component comoves with macroeconomic conditions.

4.1 Liquidity Measures

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.[18] Considering these multiple measures is important because different aspects of the liquidity concept may manifest itself in different fashions 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 3 reports descriptive statistics for these liquidity measures.

4.1.1 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 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 3, 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

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

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.

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

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 3, 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 for speculative-grade bonds.

4.1.3 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.

As shown on Line 3 of Table 3, 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 4 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 multi-faceted 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.

4.1.4 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 3. 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 in bond rating. In addition, speculative-grade bonds tend to be smaller and notably older, but the remaining maturity is the longest for BBB-rated bonds and the shortest for A-rated bonds .

Figure 4 shows the distributions of bond age, remaining maturity, and maturity at issuance for the regression sample. The number of bonds decreases quickly for those older than 9 years (top panel) or those with more than 10 years of remaining maturity (middle panel). These distributions suggest that in interpreting results related to age and remaining maturity, we have to be cautious about the reliability over the range greater than 10 years. In addition, while there are wide variation in the maturity at issuance (bottom panel), about half of the bonds were issued at 10 years, with other mass points at 3, 5, 7, 15, 20, and 30 years.

4.1.5 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. It is worth to point out 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).

Table 5 presents the regression results. Note that to allow for more flexible and potentially nonlinear functional forms, we use a 4-th order polynomials for bond age and remaining maturity.[19] We also include firm and time fixed-effects to account for unobservable firm heterogeneity and

[19] 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.

macroeconomic effects. 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. Their functional forms, plotted in Figure 5, suggest that bonds that are older or have longer remaining maturities are generally more illiquid. The only exception is that turnover rate increases with term-to-maturity for speculative-grade bonds.

4.1.6 Correlations between Nondefault Component and Liquidity Measures

Before presenting our main regression results, we examine how the nondefault components are related unconditionally to our liquidity measures. Table 6 shows pairwise correlations between nondefault components with swap rate and liquidity measures for each rating group. The results with Treasury rate, not shown, are similar.

For AA- and A-rated bonds, the correlations between the nondefault component and transaction-based measures are statistically significant and have expected signs. Specifically, the correlations are positive with the Amihud and bid-ask measures and negative with turnover rate. For BBB-rated and speculative-grade bonds, the correlations with turnover rate are significant and negative, as expected, but statistically insignificant with the Amihud measure and negative with the bid-ask measure. Overall, all correlations are generally low, with the strongest (in absolute values) being those between the nondefault component and turnover rate, -36 percent, for BBB-rated bonds.

The correlations between the nondefault component and bond characteristics are more consistent across bond ratings. The nondefault component tends to be larger for bonds with higher coupon, older age, longer remaining maturity, or smaller size. Again, all correlations are moderate with the strongest (in absolute values) being those between the nondefault component and bond size, −39 percent, for both BBB-rated and speculative-grade bonds.

4.2 Regression Results

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. Third, we test whether our key results are affected by controlling for conventional liquidity proxies. Finally, we present results from a number of analyses for robustness, including explicitly controlling for macroeconomic conditions and using Treasury rate as the risk free rate. 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.

4.2.1 Controlling for Unobservable Firm Heterogeneity

Table 7 reports the results from OLS regressions of the nondefault component for four broad rating categories. For each sample, we first regress the nondefault component on each of our three transaction-based liquidity measures, and then on all three measures together. For each regression, we include dummy variables indicating the month of each observation as controls 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 appear to be 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 biase 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 each of the above models, where a firm is represented by a unique Merrill Lynch ticker. 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 8, 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 7, 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.

4.2.2 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. In particular, this requires that the CDS market is perfectly liquid. While the CDS market may be arguably 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), it is still evolving and its liquidity may have been varying over time. Indeed, some recent studies suggest that the effect of CDS illiquidity on CDS spreads may be positive and statistically significant (Tang and Yan, 2007; Nashikkar and Subrahmanyam, 2006). Thus, in the presence of CDS illiquidity, our CDS-based method may have underestimated the nondefault component of yield spreads. 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 should 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.

The results with these two additional controls are shown in Table 9. 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, more 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 9 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 10. Overall, in basis points, turnover rate has the largest impact, ranging from -1.5 to -2.6 basis points; bid-ask spread comes the second, about 1 to 2 bps; and the Amihud measure is slightly smaller, about 1 to 1.5 bps. Relative to the median yield spreads for the regression samples, the liquidity effects range from 4 to 10 percent (in absolute values). These calculations 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.

4.2.3 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 9, 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. As plotted in the top panel of Figure 6, 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 about the first four years but then increase in age. As shown in the bottom panel, for investment-grade bonds, nondefault components are higher for the first couple of years of remaining maturity and then remain roughly flat; 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 unobservable firm heterogeneity are not well controlled for, those findings may just reflect the correlation between bond size or maturity and credit risk.

4.2.4 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, historical volatilities, and implied volatilities on the S&P

500 index; and the on-the-run spread for 10-year Treasury securities.

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). However, this interpretation should be taken with a grain of salt, considering that the recent behavior in the Treasury term structure, especially its inverting yield curve, is still not well understood. Finally, nondefault components are found to increase in S&P implied volatility but decrease in the historical volatility, possibly because implied volatility is forward looking. Results on 10-year Treasury on-the-run premium are only positively significant for AA-rated bonds, as they may be closer substitutes for Treasury securities.

4.2.5 Robustness Analysis

This section presents a number of exercises that check for the robustness of our results. These include: (1) constructing our transaction-based liquidity measures using trades that occurred in the time window less subjected to news; (2) using Treasury rate as the risk free rate measure in estimating the nondefault component; and (3) using the nondefault component estimated without adjusting for coupon effects. Overall, our results are robust to these alternative model specifications, estimation methods, and samplings.

Liquidity Measures Estimated Using "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.

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.

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.

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 3).

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.

5 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 macroeconomic conditions—negatively with the Treasury term structure and positively with the stock market implied volatility (VIX). In addition, controlling for conventional liquidity proxies does not affect the statistical significance of our transaction-based liquidity measures, suggesting our 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 tax on corporate yield spreads.

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Appendix

A 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.[20]

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.

[20]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.

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
≤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[a]	1263	328	808	242

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

[a]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: **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.[a] 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

[a]The choice of three months appears to be ad hoc. But the results with more restricted sampling such as by removing bonds that appear in less than 12 months are similar. The results without such restriction at all are also similar except for BB-rated bonds.

Table 3: **Descriptive Statistics for 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 jth trade of bond i on date t. Amihud measure of the jth 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 (N. of Obs.)*	**All** (15270)						**AA** (2332)			**A** (7615)			**BBB** (2927)			**High-yield** (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

* The numbers of observations for the liquidity measures may be smaller than stated on this line.

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

Table 4: **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 5: **Relationship between Transaction Based Liquidity Measures and Liquidity Proxies**

(1) Liquidity variables are defined as shown in Table 3. (2) Each column is a regression model of the form:

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

where [il]liquidity measure used for the corresponding model is indicated in the row under the column numbers. Polynomials of order 4 are used for bond age and remaining maturity in each model. The results of tests of joint significance of the age coefficients and the remaining maturity coefficients are shown here, and their functional forms are plotted in Figure 5. (3) Figures in parentheses are robust standard errors. (4) * 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	-0.082**	-0.040**	-0.044*	-0.056**	0.0035	-0.066**	-0.035	0.0029	-0.078**	-0.29**	-0.028	-0.072*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.008)	(0.01)	(0.05)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)
Log(Bond size)	0.20**	-0.068**	0.28**	0.27**	-0.059**	0.35**	-0.0044	-0.092**	0.26**	0.43**	0.099	0.064
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.08)	(0.03)	(0.06)	(0.2)	(0.06)	(0.08)
Bond age/10	2.91**	0.96**	-4.21**	2.88**	0.32*	-3.43**	4.83**	1.66**	-3.22**	5.75**	2.43**	-0.98
	(0.4)	(0.2)	(0.4)	(0.4)	(0.2)	(0.3)	(0.9)	(0.5)	(0.6)	(1.6)	(0.7)	(0.7)
$(\text{Bond age}/10)^2$	-2.47**	-0.72	5.69**	-2.11**	0.52	4.92**	-5.75**	-2.57**	4.13**	-5.66*	-3.19**	0.23
	(0.8)	(0.5)	(0.8)	(0.7)	(0.4)	(0.6)	(1.9)	(1.1)	(1.3)	(3.0)	(1.3)	(1.4)
$(\text{Bond age}/10)^3$	1.06**	0.17	-3.18**	0.72	-0.62**	-2.90**	3.40**	1.70**	-2.24**	3.19	1.94**	0.32
	(0.5)	(0.3)	(0.6)	(0.5)	(0.3)	(0.5)	(1.3)	(0.7)	(0.9)	(2.0)	(0.9)	(1.0)
$(\text{Bond age}/10)^4$	-0.20*	-0.019	0.59**	-0.12	0.13**	0.54**	-0.68**	-0.34**	0.41**	-0.69*	-0.40**	-0.097
	(0.1)	(0.07)	(0.1)	(0.09)	(0.06)	(0.09)	(0.3)	(0.1)	(0.2)	(0.4)	(0.2)	(0.2)
Term-to-mat/10	2.65*	3.76**	-4.78**	1.97**	2.16**	-5.35**	6.98**	3.57**	-1.04	1.15	3.63**	4.81**
	(1.4)	(0.9)	(1.5)	(1.0)	(0.5)	(0.8)	(2.9)	(1.3)	(1.8)	(3.4)	(1.8)	(1.9)
$(\text{TTM}/10)^2$	-1.95	-5.83**	11.7**	1.91	-0.93	12.4**	-11.6	-4.22	3.14	6.31	-3.81	-7.14
	(3.8)	(2.4)	(4.3)	(2.6)	(1.4)	(2.2)	(8.0)	(3.6)	(4.8)	(9.0)	(4.8)	(5.0)
$(\text{TTM}/10)^3$	1.08	5.38**	-11.8**	-4.97*	-0.58	-11.2**	9.03	2.15	-2.76	-12.7	0.45	5.14
	(4.0)	(2.6)	(4.7)	(2.7)	(1.5)	(2.3)	(8.8)	(3.9)	(5.0)	(9.2)	(4.8)	(5.0)
$(\text{TTM}/10)^4$	-0.37	-1.88**	3.94**	2.16**	0.40	3.40**	-2.70	-0.38	0.61	5.60*	0.54	-1.41
	(1.4)	(0.9)	(1.7)	(0.9)	(0.5)	(0.8)	(3.2)	(1.4)	(1.8)	(3.1)	(1.6)	(1.7)
Constant	-3.17**	-0.026	-3.41**	-3.50**	-0.041	-3.56**	-2.36**	-0.18	-3.03**	-3.49**	-1.10**	-4.37**
	(0.3)	(0.2)	(0.3)	(0.3)	(0.1)	(0.2)	(0.7)	(0.3)	(0.5)	(1.3)	(0.5)	(0.6)
Observations	2185	2050	2138	6497	5751	6689	2135	1603	2214	1266	916	1366
Number of firms	20	19	19	82	77	81	95	83	99	61	59	66
R^2	0.22	0.36	0.26	0.13	0.26	0.19	0.12	0.20	0.11	0.12	0.13	0.16

Table 6: **Pairwise Correlations between Nondefault Components of Bond Spreads and Liquidity Measures**

This table shows the pairwise correlations between nondefault components of bond spreads (with swap rate) and liquidity measures and proxies for each bond rating group. See Table 3 for variable definitions. * indicates the correlation coefficient is statistically significant at the 95 percent confidence level.

	Corr(nondef. comp. with swap rate, liquidity measure)			
Correlation with	AA	A	BBB	High-yield
Transaction-based measures				
Amihud	0.17*	0.07*	-0.03	-0.08*
Bid-ask	0.19*	0.11*	-0.18*	-0.19*
Turnover	-0.13*	-0.13*	-0.36*	-0.25*
Bond char. as proxies				
Coupon	0.30*	0.28*	0.07*	0.07*
Bond size	-0.08*	-0.10*	-0.39*	-0.39*
Age	0.22*	0.20*	0.19*	0.05*
Term-to-maturity	0.12*	0.07*	-0.01	0.03

Table 7: **Results of OLS Regressions of Nondefault Bond Spreads on Bond Liquidity Measures with Time Fixed Effects**

(1) Brief variable definitions are in Table 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

(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)
Observations	2185	2050	2138	1914	6497	5751	6689	5182	2135	1603	2214	1320	1266	916	1366	824
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

Table 8: **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 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

(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)
Observations	2185	2050	2138	1914	6497	5751	6689	5182	2135	1603	2214	1320	1266	916	1366	824
Number of firms	20	19	19	18	82	77	81	75	95	83	99	75	61	59	66	58
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

Table 9: **The Effects of Bond Liquidity on the Nondefault Bond Spreads by Controlling for CDS Liquidity**

(1) Brief variable definitions are in Table 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

(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.)	0.44			0.52	0.70**			0.56**	0.69**			0.58	-0.17			-0.0025
	(0.3)			(0.3)	(0.1)			(0.2)	(0.2)			(0.4)	(0.4)			(0.6)
Log(Bid-ask spreads)		1.30**		0.57		1.89**		1.09**		1.39**		-0.47		-0.56		-0.075
		(0.5)		(0.6)		(0.3)		(0.3)		(0.5)		(0.6)		(1.2)		(1.4)
Log(Turnover rate)			-1.35**	-1.27**			-1.00**	-0.75**			-1.20**	-1.30**			-0.54	-0.78
			(0.2)	(0.2)			(0.2)	(0.2)			(0.3)	(0.4)			(0.8)	(1.1)
N. of CDS quotes	-0.15	-0.15	-0.037	-0.10	0.41**	0.36**	0.40**	0.40**	0.040	0.33*	0.038	0.56**	0.22	0.030	0.34	0.23
	(0.09)	(0.10)	(0.09)	(0.10)	(0.07)	(0.08)	(0.07)	(0.08)	(0.1)	(0.2)	(0.1)	(0.2)	(0.3)	(0.3)	(0.3)	(0.4)
Lagged CDS spread	0.08**	0.07**	0.09**	0.08**	-0.03**	-0.03**	-0.02	-0.03**	-0.17**	-0.18**	-0.16**	-0.17**	-0.13**	-0.12**	-0.13**	-0.11**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	1.36	-4.91	-8.64*	-9.69*	8.06*	7.76*	1.86	-14.8**	28.2**	28.7**	25.2**	21.5**	317**	80.0**	-23.4**	-22.4**
	(4.1)	(5.8)	(4.5)	(5.5)	(4.7)	(4.4)	(4.3)	(3.6)	(2.1)	(2.7)	(2.0)	(2.9)	(26)	(14)	(7.6)	(10.0)
Observations	1987	1868	1949	1759	6068	5401	6259	4911	1940	1468	2007	1225	1059	756	1139	684
Number of firms	19	18	18	18	77	76	77	73	86	76	87	69	57	52	59	52
R^2	0.12	0.13	0.14	0.15	0.14	0.15	0.14	0.16	0.25	0.27	0.25	0.29	0.32	0.30	0.30	0.30

Table 10: **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 9. 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		1.03	1.46		4.1	2.4
		[0.74, 1.31]	[0.63, 2.28]		[3.0, 5.2]	[1.0, 3.7]
2. Bid-ask spread	0.97	1.73	1.53	6.5	6.9	2.5
	[0.24, 1.70]	[1.20, 2.27]	[0.46, 2.60]	[1.6, 11.3]	[4.8, 9.1]	[0.7, 4.3]
3. Turnover rate	-1.48	-1.79	-2.64	-9.9	-7.2	-4.3
	[-1.91, -1.05]	[-2.49, -1.09]	[-3.92, -1.35]	[-12.7, -7.0]	[-10.0, -4.4]	[-6.4, -2.2]
Memo. Median in basis points for regression samples:						
4. Yield spread[a]	15	25	61			
5. Nondefault comp.[b]	-1.25	-1.37	5.00			

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

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

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

(1) Brief variable definitions are in Table 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

Polynomials of order 4 are used for bond age and remaining maturity in each model. The results of tests of joint significance of the age coefficients and the remaining maturity coefficients are shown here, and their functional forms are plotted in Figure 6. (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.)	-0.024			0.100	0.40**			0.18	0.45**			0.23	-0.40			-0.28
	(0.2)			(0.3)	(0.1)			(0.2)	(0.2)			(0.3)	(0.4)			(0.6)
Log(Bid-ask spreads)		0.66		0.37		1.17**		0.93**		1.14**		0.26		-0.77		0.32
		(0.5)		(0.5)		(0.3)		(0.3)		(0.5)		(0.6)		(1.2)		(1.4)
Log(Turnover rate)			-0.68**	-0.52**			-0.36**	-0.23			-0.61**	-0.68*			0.56	0.33
			(0.2)	(0.3)			(0.2)	(0.2)			(0.3)	(0.4)			(0.8)	(1.1)
N. of CDS quotes	-0.17**	-0.20**	-0.055	-0.16*	0.36**	0.35**	0.35**	0.36**	0.08	0.41**	0.11	0.61**	0.21	0.10	0.31	0.32
	(0.08)	(0.09)	(0.08)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.1)	(0.2)	(0.1)	(0.2)	(0.3)	(0.3)	(0.3)	(0.4)
Lagged CDS spread	-0.08	-0.08	-0.10	-0.08	-0.06**	-0.05**	-0.04**	-0.05**	-0.14**	-0.16**	-0.14**	-0.16**	-0.10**	-0.09**	-0.10**	-0.09**
	(0.07)	(0.08)	(0.07)	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Coupon	1.14**	1.04**	1.03**	0.92**	2.01**	1.89**	1.91**	1.90**	2.37**	2.69**	2.21**	2.14**	4.16**	4.48**	3.62**	4.65**
	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)	(0.2)	(0.5)	(0.5)	(0.5)	(0.6)	(1.1)	(1.3)	(1.0)	(1.4)
Log(Bond size)	-0.60*	-0.49	-0.31	-0.27	-0.030	0.082	0.024	0.28	-0.31	-0.16	0.40	0.87	-3.62	-2.92	-2.46	-3.20
	(0.3)	(0.4)	(0.3)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)	(1.0)	(1.1)	(1.0)	(1.1)	(2.2)	(2.7)	(2.0)	(2.9)
Constant	16.2**	11.4**	7.11	8.70	-3.33	14.0**	13.2**	-7.12	42.4**	45.1**	38.6**	38.8**	253**	-19.4	-23.7	-14.7
	(5.3)	(5.5)	(5.2)	(5.5)	(4.3)	(5.1)	(5.0)	(4.7)	(9.5)	(11)	(9.4)	(12)	(28)	(21)	(15)	(23)
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
Observations	1987	1868	1949	1759	6068	5401	6259	4911	1940	1468	2007	1225	1059	756	1139	684
Number of firms	19	18	18	18	77	76	77	73	86	76	87	69	57	52	59	52
R^2	0.29	0.31	0.30	0.32	0.25	0.25	0.24	0.26	0.37	0.40	0.37	0.41	0.37	0.36	0.35	0.36

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

(1) Brief variable definitions are in Table 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

(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.)	-0.041			0.066	0.48**			0.24	0.33*			0.23	-0.37			-0.18
	(0.2)			(0.3)	(0.1)			(0.2)	(0.2)			(0.3)	(0.4)			(0.6)
Log(Bid-ask spreads)		0.66		0.41		1.24**		0.96**		1.17**		0.38		-1.42		-0.34
		(0.4)		(0.5)		(0.3)		(0.3)		(0.5)		(0.6)		(1.2)		(1.4)
Log(Turnover rate)			-0.55**	-0.38			-0.28*	-0.17			-0.39	-0.23			0.81	1.14
			(0.2)	(0.3)			(0.2)	(0.2)			(0.3)	(0.4)			(0.7)	(1.2)
6-Month T-bill	-4.52**	-4.37**	-4.81**	-4.61**	-5.62**	-5.61**	-5.51**	-5.48**	-6.20**	-4.83**	-6.14**	-5.25**	-6.69**	-4.34	-4.37	-2.40
	(0.7)	(0.8)	(0.8)	(0.8)	(0.5)	(0.5)	(0.5)	(0.5)	(1.1)	(1.2)	(1.0)	(1.3)	(3.2)	(3.8)	(3.0)	(4.0)
Treas term spread	-6.72**	-6.82**	-7.18**	-7.04**	-8.12**	-8.14**	-8.16**	-8.23**	-7.60**	-5.96**	-6.94**	-6.62**	-7.20*	-3.56	-4.01	-2.17
	(0.9)	(1.0)	(0.9)	(1.0)	(0.6)	(0.7)	(0.6)	(0.7)	(1.4)	(1.5)	(1.3)	(1.6)	(4.2)	(4.8)	(3.9)	(5.1)
S&P 500 Return	5.80*	4.84	7.46**	6.27*	-7.29**	-8.17**	-4.75**	-7.71**	-2.21	-2.74	-3.91	-6.97	-34.8	-31.1	-21.1	-11.2
	(3.1)	(3.3)	(3.2)	(3.4)	(2.3)	(2.4)	(2.3)	(2.5)	(5.6)	(5.9)	(5.5)	(6.4)	(24)	(32)	(24)	(32)
S&P500 real. vol.	-9.14**	-9.32**	-9.17**	-8.99**	-6.22**	-5.43*	-5.87**	-5.15*	-17.4**	-13.1**	-19.2**	-17.4**	-0.72	-1.34	-9.55	-3.72
	(2.9)	(2.9)	(3.0)	(3.1)	(2.5)	(2.8)	(2.6)	(2.8)	(4.6)	(5.4)	(4.5)	(6.0)	(10)	(11)	(8.5)	(11)
S&P impl. vol.	0.44**	0.40**	0.51**	0.43**	0.24*	0.09	0.26**	0.16	0.70**	0.76**	0.67**	0.89**	0.24	-0.26	-0.14	-0.14
	(0.2)	(0.2)	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)	(0.3)	(0.3)	(0.3)	(0.3)	(0.6)	(0.7)	(0.5)	(0.7)
Treas. liquidity	0.22**	0.24**	0.26**	0.27**	0.092	0.11	0.096	0.14	0.12	0.12	0.052	0.11	-0.61	-0.80	-1.11**	-0.67
	(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)	(0.6)
Constant	38.2**	39.8**	35.7**	37.8**	44.2**	44.3**	41.0**	42.4**	62.7**	54.8**	59.8**	50.7**	41.7**	21.8	31.9*	17.3
	(4.9)	(5.1)	(4.8)	(5.4)	(4.0)	(4.2)	(3.9)	(4.4)	(11)	(12)	(10)	(14)	(19)	(24)	(18)	(26)
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	1987	1868	1949	1759	6068	5401	6259	4911	1940	1468	2007	1225	1059	756	1139	684
Number of firms	19	18	18	18	77	76	77	73	86	76	87	69	57	52	59	52
R^2	0.24	0.25	0.24	0.26	0.17	0.17	0.17	0.18	0.26	0.27	0.26	0.27	0.24	0.25	0.27	0.26

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

(1) Brief variable definitions are in Table 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

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 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

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 3 with details shown in the main text. (2) Each column reports the result of the following regression:

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

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: **Estimating Components of Bond Spreads: An Example**
Our estimation approach has three steps. For each issuer on each day, (1) add swap rate to observed CDS premiums and fit a par yield curve using piecewise cubic Hermite interpolating polynomial algorithm (Duffie (1999), Duffie and Liu (2001)); (2) from the estimated par yield curve, compute zero yield curve and discount rate curve using the standard bootstrap method; (3) use the discount rate curve to price all of the issuer's bonds and calculate their CDS-implied yields. The difference between bond yield and the CDS-implied yield is our estimate for nondefault component of bond spread. Default component is simply equal to bond spread minus nondefault component.

Our example is Coca-Cola Inc. on April 30, 2007 when the firm had 7 bonds outstanding. All bonds are A-rated, and their CUSIP (all with prefix 191219), coupon, and maturity date are: BM, 4.375, 15SEP2009; BP, 4.25, 15SEP2010; BJ, 6.125, 15AUG2011; AN, 8.5, 01FEB2012; BB, 7.125, 01AUG2017; AV, 0, 20JUN2020; and AP, 8.5, 01FEB2022.

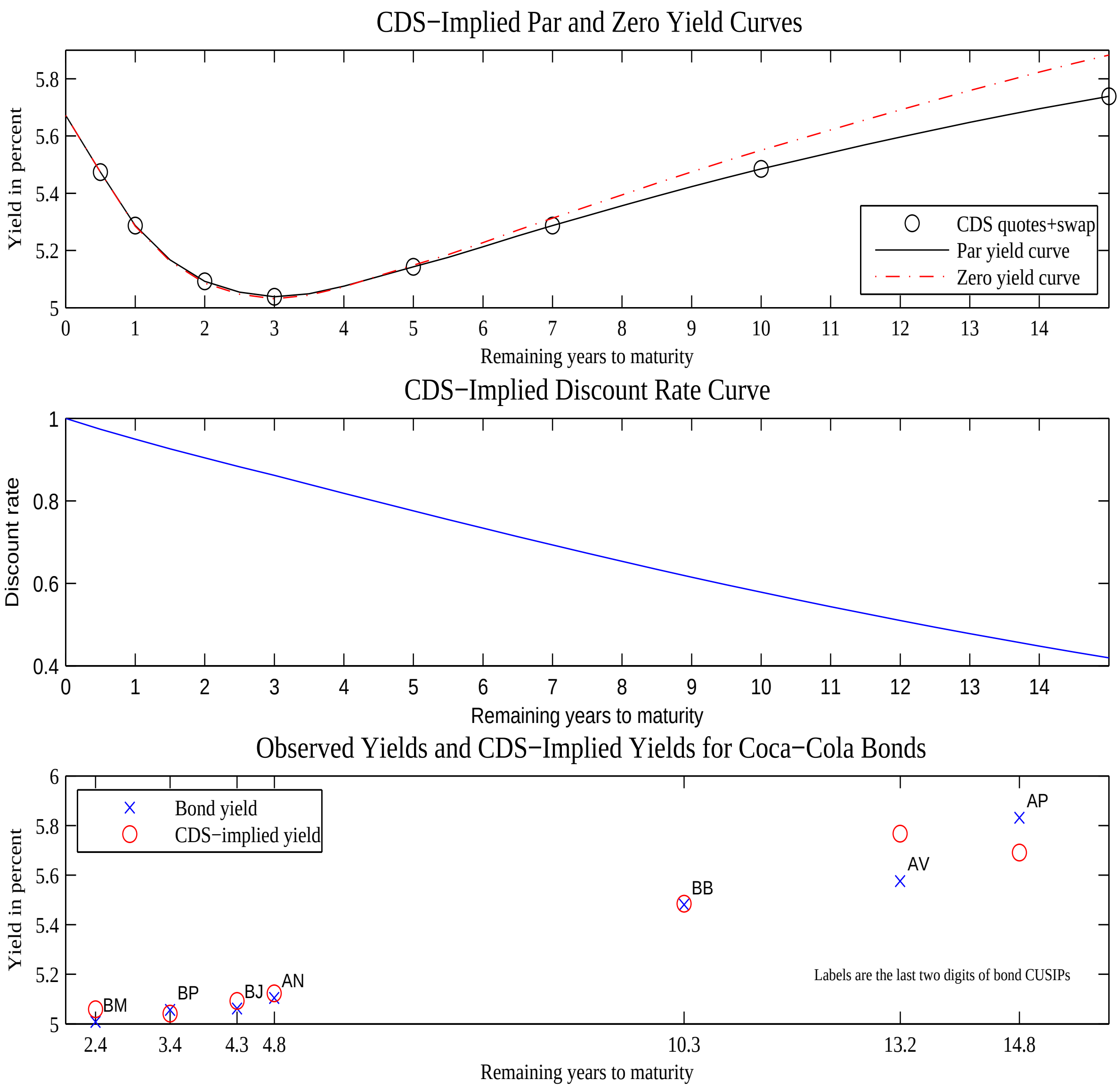

Figure 2: Cross-Sectional Distribution of Nondefault Components of Corporate Bonds

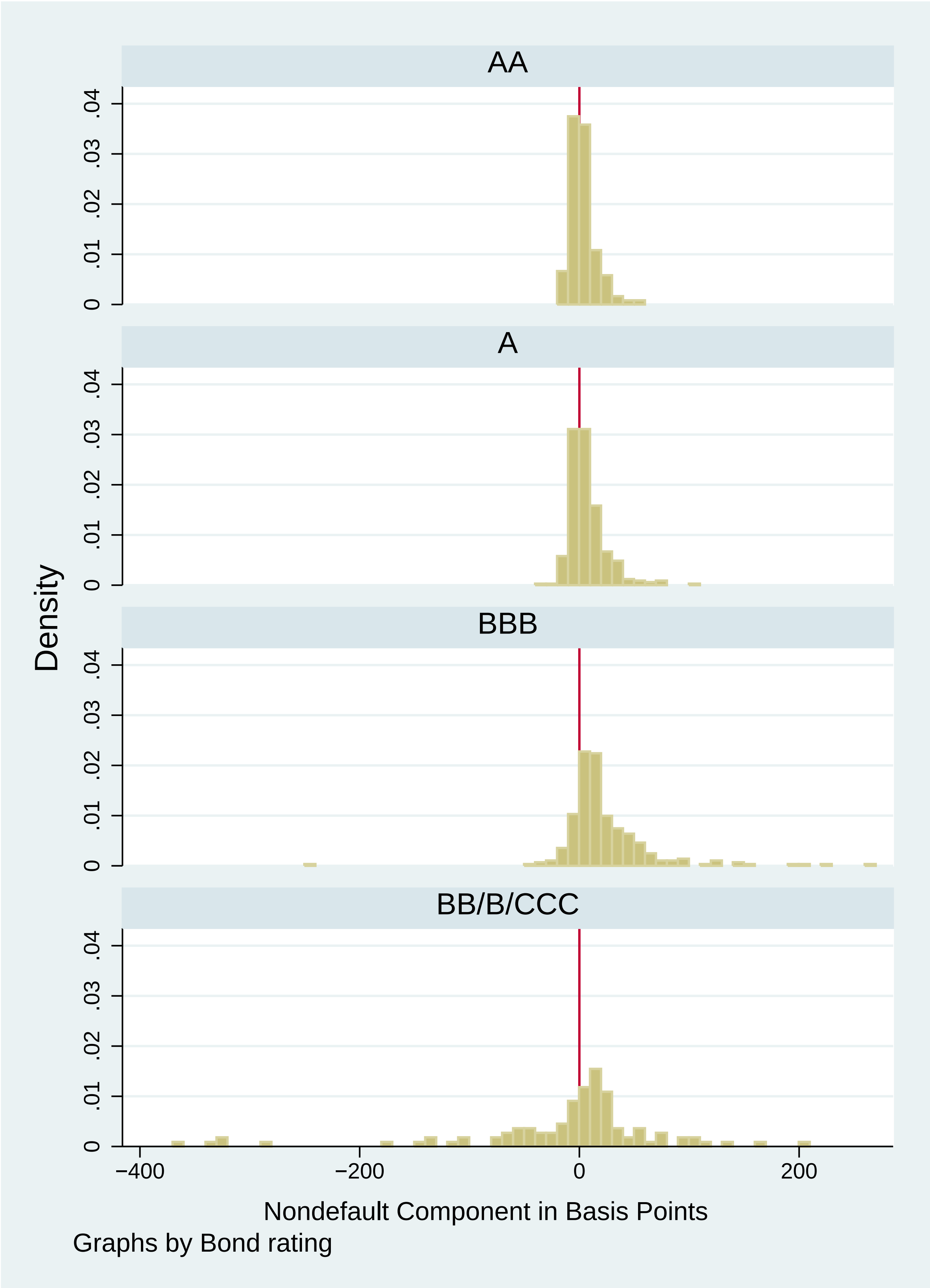

Figure 3: Time Series of Nondefault Components of Corporate Bond Spreads

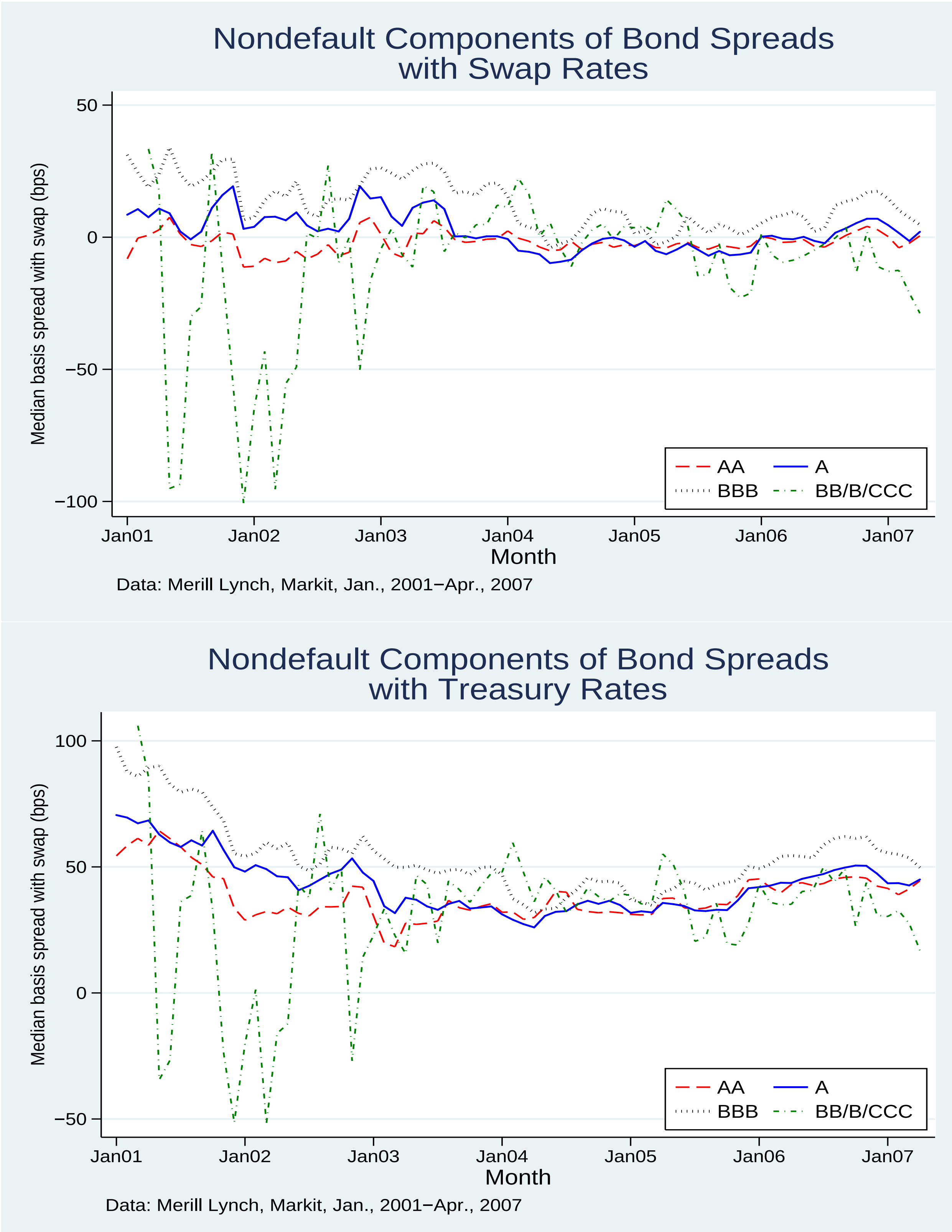

Figure 4: Distributions of Bond Age, Remaining Maturity, and Maturity at Issuance

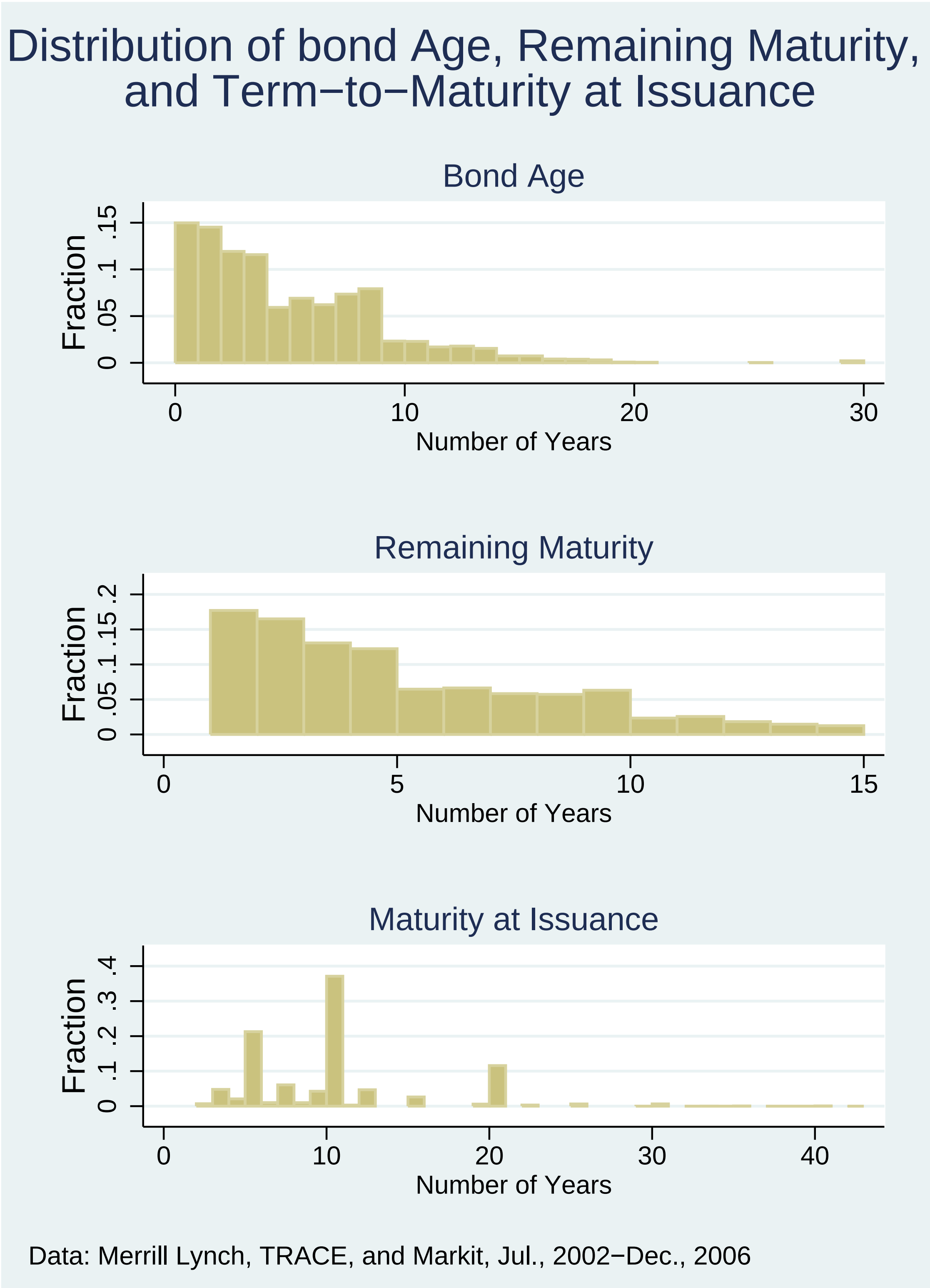

Figure 5: Relations between Trading Liquidity Measures and Bond Age and Remaining Maturity

This figure plots trading liquidity measures as 4th-order polynomials in bond age and in remaining term to maturity based on the coefficients estimated in Table 5.

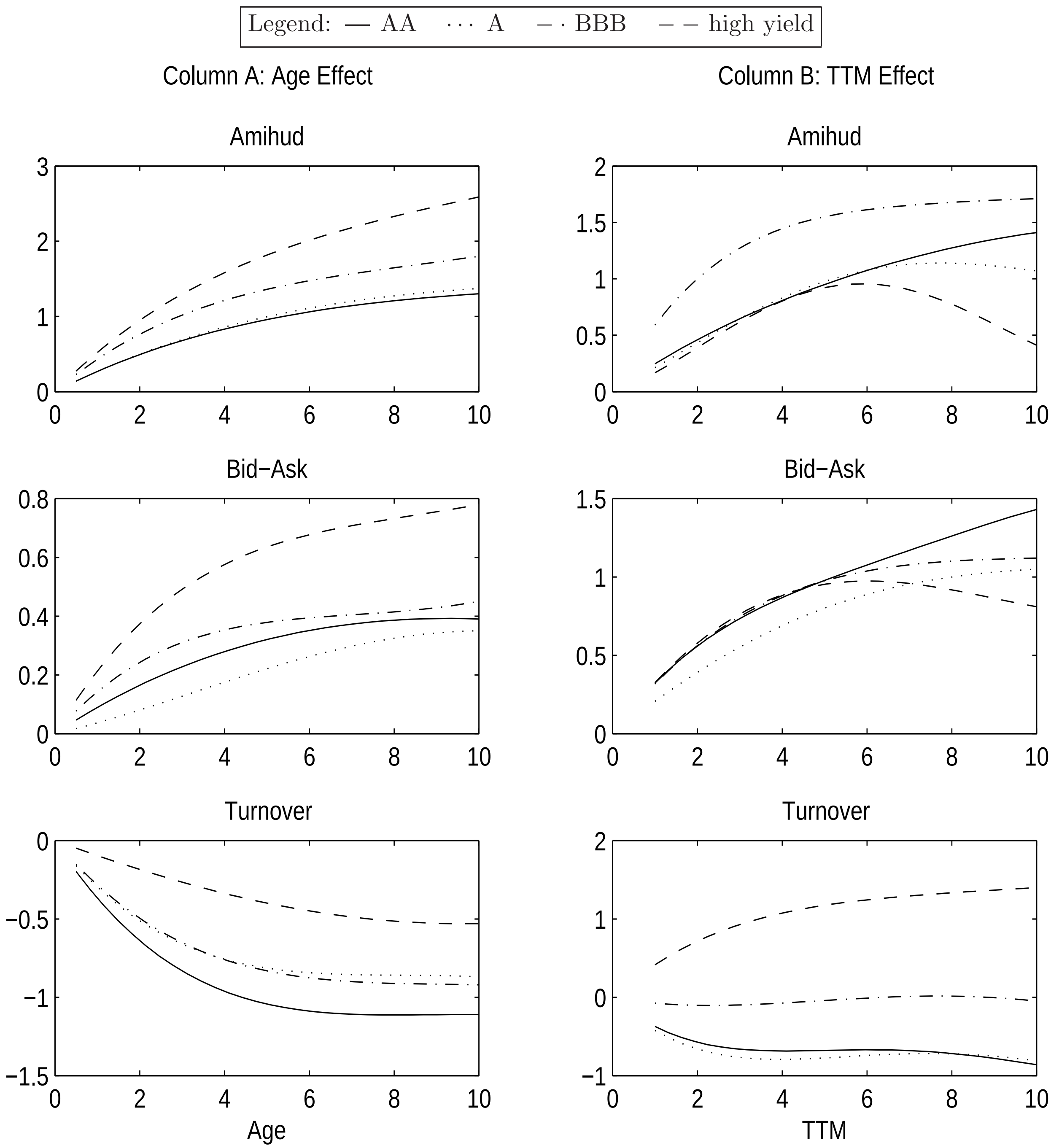

Figure 6: Relations between Nondefault Spreads and Bond Age and Remaining Maturity

This figure plots basis spreads as 4th-order polynomials in bond age and in remaining term to maturity based on the coefficients estimated in Table 9.

Legend: — AA ··· A –· BBB – – high yield