Implied Bond Liquidity*

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Abstract

We propose a new class of implied liquidity measures (ILMs) for bonds with limited transaction data by combining multiple approaches to measuring liquidity and datasets – heretofore only used separately. Generated by aggregating a bond's owners' liquidity preferences – revealed by the average liquidity of their bond holdings – ILMs are strongly robust. The high frequency of ILMs allows us to explicitly quantify a bond's systematic liquidity risk in the sense of Acharya and Pedersen (2005). We find liquidity risk to have a significant effect on bond spreads, incremental to that of liquidity level. Both effects dramatically increase during the current financial crisis.

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Liquidity, or the ease with which a security can be traded, has potentially wide ranging effects on financial markets, including direct effects on the pricing of securities. Empirical investigations of liquidity face a number of significant hurdles. First, there are considerable empirical challenges involved in constructing reliable measures of *liquidity level* for illiquid securities, given that most commonly used metrics of liquidity rely solely on transaction information. Second, the lack of high-frequency estimates of liquidity levels hampers attempts to correlate innovations of individual securities' liquidity with that of market (return or liquidity) factors, required to investigate the role of *systematic liquidity risk* in determining asset prices.[1] The importance of accessing powerful measures of innovations in liquidity is highlighted by Acharya and Pedersen (2005), who show that investors are concerned about the average level (liquidity level) as well as the timing (liquidity risk) of trading costs.

In this paper, we address these challenges in the context of one important, but relatively illiquid market, the U.S. corporate bond market. We combine data from multiple publicly available sources: bond holdings information, obtained from the National Association of Insurance Commissioners (NAIC) and Morningstar Direct (MD), and bond transactions data made available by the Trade Reporting and Compliance Engine (TRACE) and the Mergent Fixed Income Securities Database (FISD). Other studies of bond liquidity only use a subset of our datasets.

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[1] This measurement problem is prevalent in both bond and equity markets. To our knowledge, no studies have been able to explicitly measure individual bonds' systematic liquidity risk and quantify its impact on bond spreads. In equity contexts, Bekaert et al. (2007) face similar challenges in investigating the linkage between liquidity and expected returns of equities in emerging markets.

Specifically, we propose a new class of implied liquidity measures (ILMs) which belong to a broad family of non-transaction based measures, first proposed by Mahanti et al. (2008), computed by aggregating bond owners' liquidity preferences,[2] revealed by the average liquidity of their bonds' holdings. To measure a given bond's *liquidity level*, we implement the following steps:

1. First, we trace a given bond issue to the portfolios of investors $(I_1, I_2 \ldots I_K)$ holding the bond, using data from NAIC and MD.
2. Second, for each bond j owned by any of the investors identified in step 1, where data are available, we apply conventional transaction-based methods, using data from TRACE and FISD, to compute a measure of liquidity level for bond j.
3. Third, for each investor, I_k, identified in step 1, we compute a portfolio-level measure of liquidity, λ_k^P, as a weighted average of individual securities' liquidity level, obtained from step 2. To award statistical precision, we weight each security by the number of data points available in computing its liquidity level. λ_k^P is our proxy for investors' liquidity preferences.

[2] Justification of these measures requires the existence of liquidity (level) preferences, supported by an extensive theoretical literature which includes, among others, Garman (1976), Stoll (1978), Amihud and Mendelson (1980), Amihud and Mendelson (1986), Vayanos and Wang (2005), and Duffie et al. (2005). For example, Amihud and Mendelson (1986) show that, in equilibrium, long-horizon investors should optimally hold illiquid assets to capture the liquidity premiums. Vayanos and Wang (2005) show that short-horizon investors, in optimizing their search costs, would hold securities with (endogenously) relatively better liquidity. For an in-depth discussion of this issue, see Mahanti et al. (2008) and Amihud et al. (2005).

4. Fourth, we compute the given bond's liquidity level as a weighted average of the portfolio liquidity measures, λ_k^P, across all investors ($I_1, I_2 \ldots I_K$) with the weights proportional to their respective holdings of the bond.

It is important to emphasize that the proposed procedures do not require transaction data of the bond under consideration and therefore can be implemented even for bonds having no transaction data, such as newly issued bonds. We make up for the lack of transaction data by utilizing the liquidity estimates of other bonds (with sufficient transaction data) and connecting these estimates to the bond under consideration through the bond holdings structure of institutional investors.

We calibrate these implied liquidity measures (ILMs), employing the Amihud (2002) measure, the Roll (1984) measure and a measure of bond price dispersion (in step 2), and document that the number of individual bonds to which we can attribute an ILM far exceeds the coverage available using conventional transaction-based measures. For example, in 2003, the Amihud (2002) measure is computable for only 1388 bond issues while the coverage of the ILMs is over five times larger at 7326 issues. Most importantly, through a battery of validity tests, we show that not only do the ILMs correlate in a statistically significant manner with other liquidity proxies along both time series and cross-sectional dimensions but they are also significantly priced in bond spreads, after controlling for other traditional determinants of credit spreads.

To be clear about our contribution, Mahanti et al. (2008) use owners' turnover ratios[3] to proxy for liquidity preferences and call their measure the latent measure of liquidity.[4] The use of turnover ratios to characterize investors' liquidity preferences, a key differentiating feature of the latent measure, is, however, not without issues. First, our conversations with industry professionals reveal that bond funds managers can often employ cash management strategies that could inflate turnover ratios. Thus, it is not uncommon to see particularly high turnover ratios even in funds that are not particularly aggressive.[5] Second, although the latent measure, similar to the ILMs, does not require transaction data of a bond, its exact replication, as detailed in Mahanti et al. (2008), does require access to a unique proprietary dataset – transaction records of a large custodian bank. Third, to the extent that one can approximately replicate the latent measure through the use of a publicly available dataset, its interpretation as a measure of liquidity is not particularly robust. For example, Massa et al. (2009) construct virtually the same (latent) measure from a different dataset[6] but show that it can be alternatively interpreted as a measure of credit supply uncertainty (CSU). They find that CSU of the firm's bond investor base has a negative and significant effect on the firm's probability of issuing bonds, and a positive and significant effect on the firm's probability of issuing equity and borrowing from banks. That is, high average turnover rates discourage firms from issuing bonds. This evidence is hard to

[3] The turnover ratio is defined as the amount of assets traded as a fraction of the average balances of assets held in a portfolio during a given period.
[4] To replicate the latent measure, one can go through steps 1, 3, and 4 above (skipping step 2), replacing the portfolio-level liquidity, λ_k^P, with the turnover ratio of investor I_k.
[5] See http://news.morningstar.com/classroom2/course.asp?docId=2945&page=6&CN=COM, for example, for a warning message from Morningstar regarding the interpretation of turnover rates.
[6] Reuters' LIPPER dataset.

reconcile with the interpretation of the latent measure as a measure of liquidity.[7] Fourth, the use of turnover ratios limits the highest frequency of the latent measure to the quarterly level since institutional investors, such as mutual funds and other registered investment vehicles, often report their turnover statistics only at the quarterly frequency.

In contrast, when constructing the ILMs, we propose to replace the turnover ratio by a relatively more direct measure of liquidity preferences, revealed to us by the average liquidity of each investor's bond holdings. Our approach circumvents all the issues associated with the turnover ratio discussed above. First, since the liquidity of a bond held by *an* investor is measured using transactions by *all* investors, our measure, unlike the turnover ratio, is less subject to the cash management practices of institutional investors. Second, we rely only on publicly available data. Third, the ILMs, as subsequently shown, are strongly correlated with other liquidity proxies, both in time series and cross-section. Fourth, the ILMs can be calibrated to the monthly, or even weekly, frequencies.

From a bird's-eye view, we are able to take advantage of the latent measure, requiring no transaction data from the bond under consideration, as well as the advances in the micro-structure literature in the development of transactions-based liquidity measures. Relative to the transaction-based approaches, we offer a much broader coverage of bonds, thanks to the use of holdings information. Relative to the latent measure, thanks to the use of other well-developed liquidity measures in gauging investors' liquidity preferences as well as the wealth of transaction

[7] In addition, Johnson (2008) provides theoretical arguments, consistent with evidence provided by Massa et al. (2009), for why liquidity might not be related with the trading volume. That is, the fact that the investor base of a bond trades frequently might not be related to the liquidity of the bond at all. Rather, it may have an impact on the total liquidity risk of the bond.

data recently available with the TRACE database, we provide an empirically robust measure of liquidity level that requires only publicly available data. In other words, the power of the ILMs is obtained by synergizing multiple approaches to measuring liquidity and multiple datasets which have so far only been used separately.

More importantly, the relatively high frequency of the ILMs is crucial if we are to obtain a reliable measure of bonds' *systematic liquidity risk*.[8] To illustrate this important advantage of our approach, we calibrate the ILMs to the monthly level and construct monthly innovations in individual bonds' liquidity. We compute a liquidity risk beta for a bond as the covariance between changes in bond specific ILMs and innovations in market-level liquidity, scaled by the variance of bond market's returns over the same (24 month) time window. We also compute a second liquidity risk beta as the covariance between changes in bond specific ILMs and bond-market's returns, again scaled by the variance of bond market's returns over the same time window. These are two of the three liquidity risk betas in the liquidity-adjusted capital asset pricing model of Acharya and Pedersen (2005).[9] Data limitations have made it difficult, if not impossible, to directly derive these measures of systematic liquidity risk in the corporate bond market. While many studies, such as Chen et al. (2007), have drawn the link between the level of liquidity and bond spreads, the empirical connection between individual bonds' systematic

[8] Whereas one can, in principle, use quarterly ILMs, or quarterly latent measures, to construct liquidity innovations and beta measures of liquidity risk, each computation will need to be done over a long time window – not particularly suitable for bonds with medium maturities and typical bond data samples: our bond data span a sample period from 2002 to 2008.
[9] The third beta captures the co-movement of individual bond returns with market-wide liquidity shocks – not the focus of our study.

liquidity risk and bond spreads remains unclear.[10] With the ILMs and their associated betas, we are able to explicitly quantify a bond's systematic liquidity risk and unambiguously connect it to bonds' spreads, thereby shedding more light on the "credit risk puzzle" that corporate bond yield spreads cannot be explained by default risk alone.[11]

Specifically, we document that both liquidity levels and systematic liquidity risks are significantly related to bond yields, after controlling for credit risks, bond fixed effects, economic conditions, industry-fixed and ratings-fixed effects. Combined, liquidity level and liquidity risks account on average for between 20 to 120 basis points, depending on the time period. The liquidity premium explodes in 2007 and 2008 with the onset of the financial crisis. We also investigate the extent to which liquidity risk has an incremental effect on bond yields over and above the effect of liquidity level. We find that the incremental impact of systematic liquidity risk is by itself economically important, and is comparable in magnitude to the impact of the liquidity level. Though not a surprise, our findings, especially the exact quantification of the incremental impact of liquidity risk on bond prices, are new in the corporate bond literature and are consistent with the work of Acharya and Pedersen (2005), using equity returns. It should be stressed that while a meaningful and important empirical application in its own right, the asset pricing test provided in our paper represents but one illustration of the usefulness of the ILMs we

[10] For example, De Jong and Driessen (2006) examine liquidity risk by looking at the co-movements between bonds' returns and changes in equity market-level liquidity and the bid-ask spread of long-term U.S. treasury bonds, while Dick-Nielsen et al. (2009) examine the variance of liquidity levels, a measure of total liquidity risk. Acharya et al. (2009) study the exposure of the U.S. corporate bond returns to stock market and treasury liquidity risk, using a portfolio approach. Examples of other studies that empirically investigate the link between bonds' liquidity and bond spreads include Longstaff et al. (2005), Chen et al. (2007), Friewald et al. (2009), and Nashikka et al. (2009).
[11] For details, see, e.g., Elton et al. (2001) and Huang and Huang (2003).

propose. Potential applications that could use the ILMs include investigations of the liquidity of newly issued bonds, the liquidity of bonds with different seniority levels issued by the same firm, the liquidity of bonds issued by the same firm but at different stages, or the connection between firms' transparency and bonds' liquidity, all of which we leave for future research.

The rest of the paper is organized as follows. Section 2 discusses related papers and presents the detailed computation of the ILMs. Section 3 describes the data. Section 4 discuses validity tests of the ILMs. Section 5 presents asset pricing tests that investigate the role of liquidity level and risk on bond yields. Section 6 concludes.

I. Implied Bond Liquidity Measures

A. Related literature

The transaction characteristics of corporate debt have been covered by an extensive literature.[12] For instance, Chakravarty and Sarkar (1999), Hong and Warga (2000), Schultz (2001), and Hotchkiss et al. (2002) use the NAIC database to study corporate bond bid-ask spreads and trading volume. Hotchkiss and Ronen (1999) and Alexander et al. (2000) use the Fixed Income Pricing System database of high-yield bonds to study various aspects of corporate bond liquidity. Similarly, a new set of papers such as Edwards et al. (2007) and Goldstein et al. (2005) document corporate bond illiquidity using the TRACE database.

One of the most important aspects investigated by this expanding literature is the impact of liquidity on the yield spread of corporate bonds over riskless benchmarks. Longstaff et al.

[12] A comprehensive survey of the empirical evidence on liquidity can be found in Amihud et al. (2005).

(2005) provide some preliminary evidence on the importance of liquidity by showing that the basis between corporate bond spreads and credit default swap premia is explained by fluctuations in treasury liquidity. Chen et al. (2007) investigate the effect of corporate bonds' liquidity level on their yields using several explicit measures of bond illiquidity such as the imputed value change that is needed to induce a transaction in a bond based on the limited dependent variable model of Lesmond et al. (1999) (also known as "zero trading day measure"), the quoted bid-ask spread and the percent of zero returns for a given year.[13] After controlling for firm and bond risk characteristics, they find a positive illiquidity effect on spreads which is greater for non-investment grade bonds. Bao et al. (2009) use the TRACE data to construct the Roll (1984) measure as a proxy for liquidity and document that part of the yield spread differences across bonds is due to illiquidity. Finally, Friewald et al. (2009) use the bond price dispersion measure proposed by Jankowitsch et al. (2008), as a measure of transaction costs, and find that it explains approximately half of the market-wide yield spread changes over time during the sub-prime crisis.

More recent papers investigate the effect of liquidity risk on corporate bond spreads following the models of Pastor and Stambaugh (2003) and Acharya and Pedersen (2005). Downing et al. (2005), using a measure of corporate bond price impact similar to that of Amihud (2002), find that long-term corporate bonds have greater betas with respect to the bond illiquidity factor and that the liquidity shocks explain a large part of the time-series variation in bond

[13] Dick-Nielsen et al. (2008) implement the zero trading day measure using TRACE and find that, in contrast with the findings in Chen et al. (2007), it provides a weak proxy for liquidity. They provide evidence that this is due to the splitting of trades of illiquid bonds. They revise the zero-trading measure to take this aspect into account and find that it becomes unrealistically large.

returns. De Jong and Driessen (2005) estimate two liquidity betas of bond returns with respect to stock and bond liquidity shocks, using the stock illiquidity measure of Amihud (2002) and the quoted bid-ask spreads on long-term U.S. Treasury bonds. They find that bonds with lower ratings and longer maturities have a higher illiquidity premium. However, a relevant factor for corporate bond yields is the liquidity risk specific to the corporate bond market, since it may not necessarily be spanned by treasury bond and stock market illiquidity. Dick-Nielsen et al. (2008) improve on De Jong and Driessen (2005) study by focusing on bond market specific measures and by isolating the changing behavior of liquidity betas before and after the credit crisis. Their panel regressions based on quarterly data document a significant effect of the liquidity level and risk, which increased with the onset of the sub-prime crisis.

B. Computation of ILMs

All papers mentioned above rely on measures of liquidity level and risk which are based on the availability of bond prices and volume. However, transactions data in corporate bonds are quite sparse.[14] Most corporate bonds are traded in an opaque over-the-counter dealer market and often become absorbed in "buy-and-hold" portfolios at some point after issuance. As a result, most studies of bond liquidity, to date, are confined to investigating the more liquid segment of the corporate bond market for which sufficient prices and price changes can be observed. In the absence of direct measures of liquidity for most corporate bonds, early researchers rely on

[14] Edwards et al. (2006) show that a very small percentage of the bonds outstanding trade more than few times per year.

indirect proxies such as the bond's age and size and the industry category and the credit risk of the issuing firm.

Mahanti et al. (2008) take a novel approach to the measurement of bond liquidity, circumventing the lack of bond transactions data. Specifically, they develop a latent measure of liquidity simply as the weighted average of the turnover ratio of investors who hold the bond, in which the weights are the fractional investors' holdings. Mahanti et al. (2008) argue that high turnover investors are active traders, therefore would make liquid markets for the securities they hold. An immediate consequence of this argument is that high-turnover investors, on average, hold securities with (possibly endogenously) better liquidity. In other words, the turnover rate of an investor is informative about the liquidity of the typical securities that he/she holds.

One can further generalize the idea of Mahanti et al. (2008). From the theoretical models of Amihud and Mendelson (1986), and more recently Vayanos and Wang (2007), "clientele"-type equilibria exist whereby agents exhibit differing liquidity preferences. Long-horizon investors optimally hold illiquid assets to capture the liquidity premiums. Short-horizon investors, in optimizing search costs, hold assets that are (endogenously) relatively better in liquidity. To the extent that liquidity preferences can be measured, the liquidity of a given bond can be inferred by aggregating the liquidity preferences of its owners. Should we use turnover ratios to proxy for investors' liquidity preferences, we would arrive at the latent measure of Mahanti et al. (2008), as a special case. The use of the turnover ratios to characterize investors' liquidity preferences is, however, not without issues. We provide a description of these issues in the introduction section. To circumvent these issues, we propose to replace the turnover ratio by a relatively more direct measure of liquidity preferences, which is revealed by each investor's bond holdings: the average liquidity of bonds held in their portfolio. To be specific, we propose to measure a given bond's *liquidity level* over a given time period through a 4-step procedure:

1. First, we trace a given bond issue to the portfolios of investors $(I_1, I_2 \dots I_K)$ holding the bond at the end of the given period, using data from NAIC and MD. Detailed descriptions of these (and other) datasets are provided in the next section.
2. Second, for each bond j owned by any of the investors identified in step 1, where transaction data are available, we apply conventional transaction-based methods, using data from TRACE and FISD, to compute a measure of liquidity level, λ_j, for bond j over the given time window. The transaction-based liquidity measures used in this step will be described shortly.
3. Third, for each investor, I_k, identified in step 1, we compute a portfolio-level measure of liquidity, λ_k^P, as a weighted average of individual bonds' liquidity level, obtained from step 2. To reduce noises, we cross-sectionally rank λ_j and eliminate the top 1% extreme values from both sides. To further increase statistical precision, we weight each bond by the number of data points available in computing its liquidity level. λ_k^P is our proxy for the liquidity preference of investor I_k. To be specific:

$$\lambda_k^P = \frac{1}{\sum \omega_j} \sum \lambda_j \omega_j$$

where j indexes all bonds owned by investor I_k; λ_j is the transaction-based liquidity measure of bond j, obtained in step 2; ω_j is the number of data points used in computing λ_j.

4. Fourth, we compute the given bond's ILM, denoted by $I\lambda$, as a weighted average of the portfolio liquidity measures, λ_k^P, across all investors ($I_1, I_2 \ldots I_K$) with the weights proportional to their respective (log-transformed) holdings of the bond.[15] To be specific:

$$I\lambda = \frac{1}{\sum v_k} \sum \lambda_k^P v_k$$

where k indexes all the owners of the given bond; λ_k^P is the portfolio-level liquidity measure for investor I_k, obtained in step 3; v_k is the natural logarithm of the bond's holding by investor I_k.

We argue that the use of λ_k^P, as opposed to investors' turnover, as a proxy for investors' liquidity preferences, offers significant advantages. First, our conversations with industry professionals reveal that bond funds managers often employ cash management strategies that could inflate turnover ratios. Thus, it is not uncommon to see particularly high turnover ratios even in funds that are not particularly aggressive. In contrast, since we compute the liquidity of a

[15] Using raw holdings as weights will result in noisier averages since for many bonds, substantial holdings are concentrated in the hands of a few number of investors. The main results of the paper would remain unchanged when we use this approach.

bond using transactions by *all* investors, our measure, unlike the turnover ratio, is less subject to the cash management practices of institutional investors.

Second, while exact replication of the latent measure requires access to a proprietary dataset, transactions records of a large custodian bank,[16] the ILMs rely only on publicly available data sources. Access to bond transaction data provided by TRACE is standard and the holdings information provided by NAIC and MD can be obtained at affordable costs.[17]

Third, to the extent that one can approximately replicate the latent measure through the use of a publicly available dataset, its interpretation as a measure of liquidity is not particularly robust. Recent evidence reported by Massa et al. (2009) shows that the latent measure, constructed using the LIPPER database from Reuters, can be alternatively interpreted as a measure of credit supply uncertainty (CSU). They find that CSU of the firm's bond investor base has a negative and significant effect on the firm's probability of issuing bonds, and a positive and significant effect on the firm's probability of issuing equity and borrowing from banks. This evidence is hard to reconcile with the interpretation of the latent measure as a measure of liquidity. In addition, Johnson (2008) provides theoretical arguments, consistent with evidence provided by Massa et al. (2009), for why liquidity might not be related with the trading volume. He argues that even when the investor base of a bond trades frequently, it may not mean the bond is more liquid. This evidence suggests the need for an alternative, more robust measure of liquidity preferences. To this extent, we measure liquidity preferences with a straightforward logic: if an investor prefers to hold relatively liquid securities, that preference must be reflected

[16] We have attempted multiple times to obtain access to the same dataset without success.
[17] At the time of writing this paper, the NAIC offers a 90% discount to academic institutions.

by none other than his/her holdings. Using this direct approach, we are able to combine well-developed transactions-based measures of liquidity with the wealth of bond transaction data from TRACE, which have not been utilized by the latent measure, to be relatively more informed about investors' liquidity preferences. As a consequence, the ILMs, as subsequently shown, strongly correlate with other liquidity proxies, both in time series and cross-section. Our approach of using the portfolio's average liquidity to proxy for investors' liquidity preferences is, no doubt, imperfect. For example, in measuring portfolio-level liquidities, we are confined to using only securities with some transaction data. In addition, we can only work with a partial list of owners for any given bond issue. Nevertheless, these measurement errors (which equally impact the latent measure) can only weaken the ILMs as a liquidity measure. Therefore, the strong empirical performance of the ILMs that we document is proof of the robustness of our approach.

Fourth, the use of turnover ratios limits the highest frequency of the latent measure to the quarterly frequency since institutional investors, such as mutual funds and other registered investment vehicles, often report their turnover statistics only quarterly. On the other hand, the ILMs can be calibrated to the monthly, or even weekly, frequencies. The relatively high frequency of the ILMs is crucial if we are to obtain a reliable measure of bonds' *systematic liquidity risk*. In the sense of Acharya and Pedersen (2005), this is the extent of co-movement between the innovations of bond specific liquidity and market (return or liquidity) factors. With quarterly liquidity measures, each computation would require a period of about four to five years of uninterrupted data to construct reliable liquidity innovations and beta measures of liquidity risk. This is not suitable for bonds with medium maturities and limited trading especially when the available bond data sample spans a sample period from 2002 to 2008. In our subsequent analysis of liquidity risks, we calibrate the ILMs at the monthly frequency and use 24-month rolling windows to construct our measures of systematic liquidity risk.[18]

To close this sub-section, we would like to draw a connection between our approach and the theory of kernel regressions (see, e.g., Li and Racine (2007) and Simono (1996)) which would measure the liquidity of a given bond, with insufficient transaction data, by a weighted average of the transaction-based liquidity measures of other bonds with weights being some kernelled measure of similarity (in liquidity characteristics) between the bond under consideration and other bonds. Our approach is equivalent to the kernel regression approach, except that the weights, instead of being explicitly specified, are implicit from the holdings structure of institutional investors.

C. Transaction-based liquidity proxies underlying the ILMs

In this section, we provide a description of the transaction-based liquidity measures employed in the second step of our 4-step procedure. Due to the multiple facets of liquidity, no single measure has strictly dominated all other measures. As a result, we decide to choose three of the more popular transaction-based liquidity measures for our empirical implementation: the Amihud (2002) measure, the Roll (1984) measure, and a price dispersion measure,[19] which we

[18] We use quarterly ILMs in our analysis of liquidity level and various validation tasks.

[19] We also attempt to use the LOT measure (proposed by Lesmond et al. (1999) and used for bonds by Chen et al. (2007)) but over our sample period, the MLE implementation of the LOT measure is divergent for most of the bonds

label Amihud, Roll, and Dispersion, respectively. For each of these raw liquidity measures, we calibrate their corresponding ILMs and, for the sake of brevity, label them: I-Amihud, I-Roll, and I-Dispersion, respectively.

Amihud

Amihud (2002) constructs an illiquidity measure based on the theoretical model of Kyle (1985) to proxy for a security's market depth. The idea is that investors can trade large quantities of very liquid assets without moving their price. We compute a version of this measure as the average of daily absolute returns R_t divided by the daily trading volume:

$$\frac{1}{N}\sum\frac{|R_t|}{Daily\ Trading\ Volume} \tag{1}$$

where daily trading volume is expressed in millions of dollars. N is the number of trading days for the bond during the year. We have also computed the Amihud measures using excess returns, as opposed to raw returns. This is suggested by Downing et al. (2005) as a way to account for shifts of the term structure of interest rates. However, the two measures are highly correlated with each other. Consequently, we only use the Amihud measures computed using raw returns.

Roll

The measure suggested by Roll (1984) captures the idea that the price of an asset bounces back and forth within the bid-ask band as it is traded. Larger bid-ask bands lead to a larger negative covariance between adjacent price changes. Based on this intuition, Roll (1984)

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issues. Dick-Nielsen (2008) also report issues with the LOT measure over a similar sample period. For these reasons, we do not use the LOT measure in our analysis.

computes, under certain assumptions, the effective bid-ask spread as two times the square root of minus the covariance between adjacent price changes:

$$2 \times \sqrt{-\operatorname{cov}(R_{t-1}, R_t)} \tag{2}$$

We compute the Roll measure if the auto-covariance of returns is negative[20] and assign a missing value otherwise.

Dispersion

Feldhutter (2009) and Dick-Nielsen et al. (2009) propose the use of a bond price dispersion measure to capture roundtrip trading costs and show that this measure is at least as robust as the Amihud (2002) measure. The Dispersion measure is defined as:

$$\frac{1}{N}\sum \frac{P_{i,\max} - P_{i,\min}}{P_{i,last}} \tag{3}$$

where $P_{i,max}$ $P_{i,min}$ $P_{i,last}$ are the maximum, minimum and last trading price for bond i on a given day and N is the number of trading days. We only include trading days when at least four separate transactions are observed and when the maximal price is economically distinct from the minimal price. Note that the dispersion measure adopted in this paper is different from that proposed by Jankowitsch et al (2009). While the current dispersion measure gauges how dispersed trades occur throughout the day, Jankowitsch et al (2009)'s measure looks at how far traded prices differ relative to a valuation benchmark provided by Markit on average on a given day. The advantage of Jankowitsch et al (2009)'s approach is that only one transaction is required during a day for the computation of their measure. The advantage of the current

[20] Using one year windows, only a small fraction (5%) of bond issues exhibit positive auto-covariance of daily returns.

approach is that we do not require a valuation benchmark. However, as long as the Markit's valuation benchmark falls within the range of traded prices during a day, we expect these two measures to perform comparably.

II. Data and Descriptive Statistics

A. Bond ownership data

We combine information on the holdings of bond securities by a large set of global mutual funds from MD with observations on individual insurance companies' holdings and transactions provided by the NAIC. MD provides detailed information on which securities a fund owns, whether it holds bonds or cash, and what sectors it favors. We retrieve mutual fund bond ownership data from 28,982 global mutual funds that have at least 70% of their portfolio on fixed income investments. We match all bond holding observations, by bond issue, with FISD.[21] This database provides bond specific information such as bond-issue size, issue date, bond features, bond ratings, coupon rate and frequency, and borrower information.

To eliminate recording errors, we filter out records with incorrect bond CUSIPs,[22] records without a matching identifier in the FISD database and records where the ratio of reported fair value to par is more than three standard deviations away from the cross-sectional median for the same bond issue, at the same point in time. For cases in which multiple holdings

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[21] We initially match the NAIC holdings data with FISD by the 9 digit CUSIP identifier (most of the observations have a CUSIP number). We separately match the MD observations based on either the 9 digit CUSIP identifier or the ISIN number. When these bond level identifiers were missing, we matched the data manually by issuer name, location, bond coupon and maturity date.
[22] An example of a CUSIP validation program can be found here: http://en.wikipedia.org/wiki/CUSIP.

by the same owner of the same bond are reported over the same quarter, we use the median holdings. Bonds whose total holdings add up to more than the original issue size are eliminated. As indicated from Table I, after the cleaning process, the two bond ownership files cover, on average, about 40% of a bond's original issue size. This coverage is relatively comparable with the numbers obtained from the United Stated States Flow of Funds accounts over the same time period. For a given bond, the median (average) number of investors covered by the two databases is about 30 (43). The median (average) number of bonds owned by a typical investor covered by the two databases is 27 (66).

[Table I should be placed here.]

B. Bond transactions data

We focus on corporate bond trades retrieved primarily from TRACE over the time period from January 1, 2002 to December 31, 2008, while papers such as Chen et al. (2007) use Datastream. When analyzing liquidity, it is critical that the data are not contaminated by prices which do not represent actual trades. Dick-Nielsen et al. (2009) document that the Datastream data are contaminated by matrix pricing or other price adjustments not based on actual transactions. As a result, Datastream is not used in our analysis.

TRACE provides the trade date, bond price (as a percentage of the face value), and the size of the trade (stated as the value of the transaction in thousands of dollars).[23] The TRACE

[23] For investment grade securities, if the par value of the transaction is less than or equal to $5 million, the size will state the actual par value of the bonds traded. If the par value of the transaction is greater than $5 million, the quantity field will contain the value of "5MM+." In this case, we set the transaction value to $5 million. For High Yield and Unrated bonds the restriction will be $1 million.

dataset is already matched with Mergent in Wharton's WRDS system using the bond-issue identifier. TRACE data are relatively new. On July 2002, the National Association of Securities Deals (NASD) began to report some bond transactions through TRACE, and gradually expanded TRACE requirements in subsequent periods. By February 2005, essentially all corporate bond trades were reported through TRACE. The objective of compiling information on all over-the-counter secondary market transactions of public bonds, as mandated by the United States Securities and Exchange Commission (SEC), was to improve transparency, to provide greater regulatory insight, and to decrease transaction costs for retail and small institutional investors. Based on studies by Bissembinder et al. (2006), Edwards et al. (2007), and Goldstein et al. (2007), bond investors have benefited from the increased transparency of TRACE, via reductions in the bid-ask spreads that they pay to bond dealers when trading, particularly for smaller-size trades.

Many prior studies use bond prices from the FISD database. This database is much smaller in terms of coverage and contains bond trades reported by property and life insurers, and state insurance departments.[24] This database contains details such as trade date, bond price (as a percentage of the bond face value) and accrued interest. Schultz (2001), Hong and Warga (2000), and Campbell and Taksler (2003) estimate that insurance companies hold between 30% and 40% of corporate bonds. Because TRACE coverage of firms is not complete until February 2005, we

[24] Insurers are required to report purchases and sales of corporate bonds quarterly to NAIC (Schedule D Fillings). Insurance companies are required to report the total cost of the transaction, the par amount and the date of the transaction (Chakravarty and Sarkar, 2003).

augment our TRACE bond data with that of FISD.[25] If on a certain day a bond issue does not have any trades reported in TRACE but FISD indicates that a trade has occurred, we include the FISD trade information in our sample. In almost all cases, a missing trade in TRACE is due to the fact that TRACE does not cover that specific issue at the time. The TRACE data in earlier years are biased towards investment grade securities.[26] Excluding the FISD data from our sample would bias our analyses because we expect below investment grade bonds to be less liquid.

Our bond transaction data derived by merging the FISD database with TRACE, initially provides 5,599,355 bond-day observations. Likely erroneous price records are dropped using the following filters: (1) Price records with intra-day price movements greater than $20 (out of a $100 face value); (2) Negative prices or prices larger than prices of otherwise equivalent default-free bonds;[27] and (3) Prices with trading volume of $1 or smaller. These filters reduce the number of observations to 5,303,479. Next, we exclude all bonds with nonlinear features other than callability, non-US bonds, bonds with no issue size or offering date information, bonds with missing coupon rates, or bonds with original maturities greater than 30 years. This filter reduces our bond transactions sample to 4,054,785 observations. Excluding the year 2009 and non-

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[25] Easton et al. (2009) verify the quality of the FISD transactions data and find that differences between the bond prices reported by Mergent and the bond prices reported in TRACE over the period when the two datasets overlap (2002 - 2006) are minimal.

[26] Starting in July 2002, TRACE contains information on 498 bonds. This includes bonds with an issuance size of $1 billion and a rating of A- or better, as well as 50 representative non-investment grade bonds. In April 2003, TRACE expanded to include large BBB bonds and smaller A-rated bonds with face values between $100 million and $1 billion. After February 2005, TRACE covers all trades in the secondary over-the-counter market for corporate bonds and accounts for more than 99% of the trading volume in corporate bonds. TRACE does not cover the few bonds listed on NYSE which are also the most liquid.

[27] We compute the equivalent default-free bond prices by discounting bonds' cash flows, ignoring optionality, using the daily term-matched treasury zero yields obtained from:
http://www.federalreserve.gov/Pubs/feds/2006/200628/200628abs.html.

trading days (of the equity market), we are left with 3,872,217 observations. To avoid complications on coupon payment dates, we drop bond prices on these days. Of the remaining observations, 2,268,389 daily returns can be computed based on last trading prices, after eliminating the top 1% extreme returns (from both sides) on a daily basis. These daily returns, together with the associated trading volume, are used in the computation of the raw liquidity measures.

C. Other data

We obtain additional firm-specific data from the 2008 COMPUSTAT research files. Combining the FISD and the COMPUSTAT data involves three steps: (1) we match the CUSIPs of borrowers with bonds in the FISD to the CUSIPs of firms in COMPUSTAT, (2) for each CUSIP match we verify that the company name, industry membership and country of domicile on FISD are the same as the company name, industry membership and country of domicile on COMPUSTAT, and (3) we identify borrowers in FISD that do not have a CUSIP match in COMPUSTAT and we manually match these borrowers to COMPUSTAT firms. These manual matches are made on the basis of company name, industry membership and country of domicile. We retrieve firms' senior bond ratings from FISD, information on the dispersion of earnings forecasts from First Call and equity prices from CRSP.

III. Coverage and Validity Tests of the Implied Liquidity Measures

A. Coverage

Table II reports the coverage of the ILMs, compared to that of the raw measures. As can be seen, the ILMs significantly increase the universe of bonds for which the liquidity level can be measured. For example, in 2003, the number of bonds covered by the Amihud, Roll and Dispersion measures are 1388, 1102, and 924, respectively while the numbers for the corresponding ILMs are 7326, 7284 and 7318. The improvement of at least three times in cross-sectional coverage is universal across all years, age, maturity and rating groups in the sample.

[Table II should be placed here.]

B. Validity Tests

To examine the information content of the implied measures, we perform a battery of validation tests. First, for each year in the sample, we compute the cross-sectional correlation among the raw measures and the ILMs, at annual frequency, and report these correlations averaged over time in Table III, Panel A. On average, the I-Amihud measure is strongly correlated (correlation of 0.6863) with the Amihud measure, the empirical construct that the I-Amihud measure is supposed to mimic. Moreover, the I-Amihud measure is strongly positively correlated with the Roll, Dispersion, I-Roll and I-Dispersion measures with correlations of 0.51, 0.36, 0.51 and 0.30, respectively. Particularly, these correlations display a pattern highly comparable to its raw counterpart (the Amihud measure is correlated with the Roll, Dispersion, I-Roll and I-Dispersion measures with correlations of 0.60, 0.51, 0.40 and 0.28, respectively). Most importantly, these high correlations do not come from any single year in the sample. Figure 1 confirms that these cross-sectional correlations are comparably high across all years in the sample. Similar pictures can be observed for the other two implied measures. For example, the average correlations between the I-Roll, and I-Dispersion measures with their corresponding raw measures are equally high, at 0.6392 and 0.6356, respectively. These high correlations can be consistently observed throughout the sample.

Second, we perform the time-series version of the above exercise. That is, for each bond issue in the sample, we compute the time-series correlation among the raw and the implied liquidity measures and report the cross-sectional median correlation in Table III, Panel B. As can be seen, the time-series correlations are particularly high. For more than 50% of the bond issues, the Dispersion and I-Dispersion measures have a time-series correlation greater than 0.9554. In addition, the I-Dispersion measures also correlate with the Amihud and Roll measures (correlations 0.7913 and 0.9559 respectively) in a fashion comparable to its raw counterpart (correlations 0.7483 and 0.9370 respectively). Similar pictures can be observed for other measures.

[Table III should be placed here.]

Third, we correlate the raw measures and ILMs with bonds' fixed effects used in other studies as proxies for liquidity: coupon rate, maturity, bond age, and bond's original issue size. All correlations are computed cross-sectionally and then averaged over all years in the sample. As evident from Table III, Panel C, all three ILMs correlate with these bonds' fixed effects with signs consistent with one's expectation: positively with the coupon rate (e.g., Elton et al. (2001)), maturity, age (the on-off the run effect) and negatively with the original issue sizes. It is important to note that the ILMs, once again, mimic the correlation pattern of their raw counterparts. For example, bonds' age correlates with the Amihud, Roll and Dispersion with correlations of 0.18, 0.09 and 0.04 respectively, compared to 0.38, 0.12, and 0.03 with the I-Amihud, I-Roll and I-Dispersion measures. This similarity is rather striking given the fact that the cross-section of bonds with computable ILMs is significantly larger than that for the raw measures.

Fourth, we repeat the third test by replacing the bonds' fixed effects with the following measures: bond (return) volatility, equity (return) volatility, earnings dispersion forecasts and the zero-return frequency, all computed during the same calendar years as the liquidity measures. The correlations are reported in Table III, Panel D. The first three variables are related to the amount of uncertainty associated with the underlying issuing firms. The zero-return frequency measure, used by a number of studies as a (rough) measure of liquidity, is the fraction of trading days with no changes in bond prices. In terms of bonds' volatility and the zero-return frequency, the raw and implied measures once again display highly similar correlation patterns. In terms of equity volatility and earnings forecasts dispersion, both the raw measures and ILMs show weak correlations.

Fifth, we perform a conditional test by asking whether the ILMs have any explanatory power above and beyond that of other variables. Specifically, for each year of the sample, we run the following cross-sectional regression:

$$\textit{Raw Liquidity Measures}_{it} = \alpha + \gamma\, \textit{I-Measures}_{it} + \beta\, \textit{Control Variables}_{it} + \textit{Error}_{it} \qquad (4)$$

where the control variables include bonds' fixed effects (coupon rate, maturity, age, natural logarithm of original issue size), the leverage ratio measured as long term debt to assets ratio, equity volatility, earnings forecast dispersion, trades frequency (number of trading days over a calendar year), trading volume (as a fraction of the original issue size), industry and ratings fixed effects. The coefficient estimates with corresponding clustered-robust *t*-stats (where clustering is specified at the firms' level) and *R*-squared statistics are reported in Table IV.

[Table IV should be placed here.]

As can be seen, every coefficient estimate in each year of the sample is positive and statistically significant, suggesting that the ILMs do have information above and beyond that of the included control variables to explain variations of liquidity among different bonds. Moreover, not only does the I-Amihud measure have the incremental power to trace the Amihud measure but it can also mimic the Roll measure and the Dispersion measure much better than the control variables. For example, in 2007, the I-Amihud measure helps increase the *R*-squared statistics of the regressions explaining variations of the Amihud measure by 14% (from 39% to 53%). The incremental explanatory power with respect to variations of the Roll and Dispersion measures is also comparably high, at 14% and 10% respectively.

To get a sense of how the ILMs compare to the latent measures of Mahanti et al (2008), we construct their latent measures using our bond ownership and turnover data. In unreported results, we find that the latent measures do have statistically significant explanatory power for the cross-sectional variations of the Amihud measure but not for the Roll or the Dispersion measures. In explaining variations in the Amihud measure, the latent measure shows just an average improvement in R-squared of about 0.3%, compared to 9.8% by the I-Amihud measure. While this comparison shows the strength of the ILMs, it is important to emphasize that the relative performance of the latent measures could be specific to the quality of the database used in its construction. Mahanti et al (2008) obtain their proprietary data from a large custodian bank.

In a separate, unreported analysis, we include bond returns volatility as an additional control variable in the above regressions. The I-Amihud can still explain variations in the Amihud measures very well, yet shows no incremental explanatory power to explain variations in the Roll and Dispersions measures. This lack of explanatory power in the presence of bonds' returns volatility is hardly a surprise since it is evident in Table III, Panel D, that the Roll and Dispersion measures are strongly correlated to the volatility of bond returns.

Finally, to examine the robustness of our ILMs, we re-calibrate our implied measures using only ownership data by insurance companies and re-run all of the above tests. As noted above, insurance companies cover a significant fraction of bond ownership and are likely to have relatively well defined investment horizons and thus, by the insight of Amihud and Mendelson (1986), well defined liquidity preferences. While we do not report the results in the paper for parsimony, we are able to reproduce very similar quantitative results of all of the above tests, confirming the robustness of the ILMs.

In summary, the five tests performed so far suggest that, both unconditionally and conditionally, the ILMs do a decent job in replicating the information content of their corresponding empirical constructs which are based on bond transactions data.

IV. Asset Pricing Tests of Liquidity Level and Liquidity Risk

Acharya and Pedersen (2005) show that, in equilibrium, investors will demand premiums to hold illiquid assets (the liquidity level effect) and assets whose liquidity may co-move with general market conditions (the liquidity-risk effect). This suggests that, holding all else constant, both the liquidity level and the systematic liquidity risk could play important roles in explaining yield spread levels. While the impact of the liquidity level on bond spreads has been documented by many authors (e.g., Chen et al. (2007)), the linkage between systematic liquidity risks and bond spreads has not been studied much, mainly due to the challenges in constructing a reliable measure of systematic liquidity risk. Prior studies either focus on a different dimension of liquidity risk, the timing of bonds' returns relative to general market conditions (e.g. Acharya et al. (2009)), or have to use a total, as opposed to systematic, measure of liquidity risk (e.g. Dick-Nielsen et al. (2009)). In addition, most studies are restricted to a subset of the bond universe with sufficient transaction data.

Endowed with the ILMs, we extend the level analysis of Chen et al. (2007) to a bigger cross-section of bonds. Additionally, we construct unambiguous measures of systematic liquidity risks and perform various pricing tests that show the incremental impact of liquidity risk on bond spreads.

A. Liquidity Level Analysis

In this sub-section, we perform pricing tests by running the following cross-sectional regressions every quarter:

$$\textit{Yield Spread}_{\mathrm{it}} = \quad \alpha + \gamma\, \textit{I-Measure}_{it-1} + \beta_1\, \textit{Bond Fixed Effects}_{it} + \beta_2\, \textit{Credit Risk}_{it} + \qquad (5)$$

$$\beta_3\ \textit{Level Factor}_{it} + \beta_4\ \textit{Curvature Factor}_{it} + \beta_5\ \textit{Slope Factor}_{it} +$$

$$\beta_6\ \textit{Ratings FE}_{it} + \beta_7\ \textit{Industry FE}_{it}\ + \beta_8\ \textit{Pretax Dummies}_{it} + \varepsilon_{\mathrm{it}}$$

where i is bond issue, t is quarter, and $\textit{I-Measure}_{it-1}$ is one of the ILMs constructed earlier. The ILMs are lagged one quarter to avoid any possible endogeneity issues. In addition, we use a 4-quarter moving average version of the ILMs to avoid any possible seasonal effects. Yields are available for bond transactions originating from TRACE (most of the bond transactions come from TRACE) but not for the bond transactions in FISD. We compute the bond yields for the FISD transactions as follows. We first compute the price of an otherwise equivalent default-free bond by discounting the same structure of cash flows using the daily treasury yield curves. A bond's yield spread is then the difference in the yield to maturity of the bond and its default-free counterpart. Since we run the (cross-sectional) regressions every quarter, yield spreads are averaged over each calendar quarter for each bond issue. *Bond fixed effects* include the bond coupon, age, time-to-maturity, and issue size (e.g., Sarig and Warga (1989); Houweling et al. (2005); Longstaff et al. (2005)). We control for credit risks (*Credit Risk*) in two ways and thus present two sets of regressions for each specification. First, we compute the risk-neutral distance to default, developed by Vassalou and Xing (2004), and a measure of tangibility (Property, Plant and Equipment scaled by Total Assets) to control for loss severity. Second, we use the five-year CDS spreads, contemporaneous with the yields spreads, and their associated recovery rate obtained from Markit (we take the average spread during the quarter). The five year CDS contracts are the most liquid CDS contracts and thus likely to give the cleanest measure of default risk for a given bond. We control for general market conditions by including the level, curvature and slope factors extracted from the daily treasury zero-yield curves, averaged over each quarter. Finally, we include industry fixed effects (*Industry FE*), ratings fixed effects (*Ratings FE*), and pretax coverage dummies (*Pretax Dummies*). The pretax interest coverage is defined as the ratio of operating income after depreciation plus interest expense to interest expense (Blume et al. (1998)). The Pretax Dummies are created based on the magnitude of the interest rate coverage which has been partitioned in 4 intervals from 0 to 5, from 5 to 10, from 10 to 20, and above 20.

To avoid complications with the valuation of callable options, we follow standard practices to drop all callable bonds from our database.[28] We run these regressions every quarter from 2004:Q1 until 2008:Q2, and report in Table VI the average coefficients' estimates of the implied measures and the control variables together with their corresponding robust *t*-statistics (Fama-MacBeth accounting for the Newey-West adjustment with one lag). We exclude the last two quarters of 2008 intentionally since this period includes the Lehman crisis while our purpose is to examine the impact of liquidity on the equilibrium bond yields. We note, however, that including these two quarters would not weaken our results in this section in a significant way. Actually, many of our results will be stronger.

As can be seen, the ILMs, particularly the I-Roll and I-Dispersion measures show very strong statistical power in explaining cross-sectional variations in yield spreads with a minimum robust t-stat of 7.64 between these two measures and for both sets of credit risk controls. The I-Amihud measure is positively correlated with the yield spread but in a somewhat insignificant

[28] We do not exclude callable bonds from our validation tests because these tests do not require the use of yields spreads.

fashion when the risk-neutral distance to default is used to control for credit risk. When the contemporaneous 5-year CDS spread is used instead, the I-Amihud becomes statistically significant.

To get a sense of the economic significance of the liquidity level impact captured by our implied measures, we ask how much of the yield spread (in terms of basis points) can be attributable to the liquidity level alone, above and beyond the impact of credit risks. To answer this question, for each quarter, we first (cross-sectionally) orthogonalize the ILMs against all the controls listed above. By construction, therefore, the residuals are completely orthogonal to credit risks, as measured, and other variables. *Prices* of residual liquidity are obtained as the quarterly coefficient estimates in the cross-sectional regressions of average yield spreads of non-callable bonds on the (one-quarter-) orthogonalized lagged implied liquidity measures since they convert a given level of (residual) liquidity into yields spreads. Following a similar approach by Dick-Nielsen et al. (2009), we rank the residual components of implied liquidity every quarter and the difference between the bottom 10th percentile value and the top 10th percentile value is computed as the *quantity of residual liquidity*. The product of price and quantity gives us the *residual liquidity premium* in the bond yields.

We plot these three quantities, constructed using the three implied liquidity measures, over time in Figure 2. Averaging across the three measures, we document a liquidity premium of about 8 basis points in the first half of the sample. In the second half of the sample this liquidity premium has increased to more than 10 basis points and in the last two quarters of 2008 to 30 and 70 basis points respectively. Interestingly, this increase is largely due to an increase in the price as opposed to the quantity of illiquidity. This increasing trend is in line with the current developments of the market and findings of other studies. In evaluating the magnitude of the liquidity premium, it should be noted that the average on-off the run yield differential in the treasury market over the same time period is about 2 basis points and shoots up to 8 basis points for a short window over the last three years. Due to our orthogonalization, our default-free premiums as constructed can be interpreted as some conservative lower bounds of the yield premiums due to the liquidity level. With this in mind, and in comparison with the on-off the run treasury yield differential benchmark, the liquidity premiums documented here are economically significant.

B. Liquidity Risk Analysis

In this sub-section, we investigate the impact of liquidity risk by running the following cross-sectional quarterly regressions:

$$\begin{aligned} \textit{Yield Spread}_{\mathrm{it}} = \quad & \alpha + \gamma_1\, \textit{I-Measure}_{it-1} + \gamma_2 \textit{Risk Measure}_{it-1} + \beta_1\, \textit{Bond Fixed} \\ & \textit{Effects}_{it} + \beta_2\, \textit{Credit Risk}_{it} + \beta_3\, \textit{Level Factor}_{it} + \beta_4\, \textit{Curvature} \\ & \textit{Factor} + \beta_5\, \textit{Slope Factor}_{it} + \beta_6\, \textit{Ratings FE}_{it} + \beta_7\, \textit{Industry FE}_{it} \\ & + \beta_8\, \textit{Pretax Dummies}_{it} + \varepsilon_{\mathrm{it}} \end{aligned} \tag{6}$$

The specification is identical to equation (5) except that we have one additional independent variable that captures liquidity risk, in the spirit of Acharya and Pedersen (2005). Specifically, we construct two of their three liquidity betas: (1) β_{liq} is computed as the 24-month covariance between monthly changes in individual bond's ILMs and monthly changes in a measure of bond market's liquidity; and (2) β_{ret} is computed as the 24-month covariance between monthly changes in individual bond's ILMs and bond market's aggregate monthly returns. Both of these measures are scaled by the variance of the bond market's returns over the same time window. The first liquidity beta (β_{liq}) is due to commonality in liquidity. The expected return on a bond increases with the covariance between the bond's illiquidity and the market illiquidity because investors want to be compensated for holding a security that becomes illiquid when the overall market becomes illiquid. The second liquidity beta (β_{ret}) captures the idea that the required return is higher if the sensitivity of the bond's illiquidity to market conditions is more negative. Investors accept a lower expected return on a bond security that is liquid when the market return is down. When the market declines, investors' ability to sell easily is especially valuable and, as a result, they are willing to accept a lower bond yield if the bond has low illiquidity costs in states of poor market return. We do not compute the third beta, which interacts individual bond's returns with market's liquidity, since such computation is only feasible for bonds with intensive trading data – not the focus of our study. We also construct a measure of total liquidity risk: *Var*, computed as the 24-month window variance of the monthly implied liquidity levels of a given bond, again scaled by the variance of the bond market's returns over the same time window. A similar version of *Var* is used by Dick-Nielsen et al. (2009). In computing all three liquidity risk measures, we require that we have non-missing data for at least 18 out of the 24 months.

To compute the aggregate level of liquidity for a given month, we use a simple average of liquidity level across all bonds over the same time window. Bond market's daily return is computed by averaging the daily returns of all the bonds that trade on a given day. Monthly returns are obtained by compounding daily returns over the relevant month. Since we use three raw liquidity measures (Amihud, Roll, and Dispersion), there are at least nine different ways of computing the β_{liq} measures. For the sake of simplicity, we choose to apply the same method of measuring liquidity at the security level and at the market level, thereby, reducing to only three versions of β_{liq}, corresponding to each of the Amihud, Roll, and Dispersion measures.

Summary statistics of the ILMs and the corresponding liquidity risk measures are reported in Table V. While it is difficult to interpret the magnitude of these levels since different liquidity measures are constructed at different scales, it is interesting to examine their signs. Across the three liquidity measures, β_{liq} seems to be predominantly positive while β_{ret} negative. This suggests that, across the bond universe covered by our study, a given bond tends to become illiquid at the same time when the entire bond market becomes illiquid or when the bond market's aggregate return is low. Both of these present the types of risks for which risk-averse investors demand compensation.

[Table V should be placed here.]

[Table VI should be placed here.]

Table VII reports the results of regressing yield spreads on our systematic risk measures. Panels A and B present the results for β_{liq} as a regressor and Panels C and D present the results for β_{ret} (one panel for each set of credit risk controls). We find that the liquidity risk betas based on our implied measures, particularly the I-Roll and I-Dispersion measures, show very strong statistical power in explaining the cross-sectional variation in yield spreads above and beyond the effect of the liquidity level captured by the I-measure variables, regardless of the credit risk controls used.

[Table VII should be placed here.]

Table VIII reports the results of regressing yield spreads on the total risk measures (*Var*) in the presence of liquidity level. *Var* is expected to capture the effect of two of the three liquidity betas in the Acharya and Pedersen (2005) model as well as the idiosyncratic liquidity risk. Not surprisingly, we find that the total liquidity risk gets a positive and very significant coefficient across all ILMs and for both sets of credit risk controls.

[Table VIII should be placed here.]

To have a sense of the incremental impact of each liquidity level and liquidity risk measure above and beyond the control variables, we perform a series of othorgonalization tasks:

1. Every quarter, we regress the (one-quarter) lagged ILMs on bond fixed effects, credit risks controls (one-quarter lead 5-year CDS spreads), current market conditions, and industry and ratings fixed effects and use the residuals as a measure of residual liquidity level, free from default risks and other factors.
2. Every quarter, we regress our lagged β_{liq} on the corresponding lagged ILMs together with other controls used in step 1. We use the residuals from these regressions as a measure of residual liquidity risk β_{liq}, free from liquidity level effect, default risks, and other factors.
3. Every quarter, we regress our lagged β_{ret} on the corresponding $\beta_{liq,}$ the corresponding lagged ILMs together with other controls used in step 1. We use the residuals from

these regressions as a measure of residual liquidity risk β_{ret}, free from β_{liq}, liquidity level effect, default risks, and other factors.

4. Every quarter, we regress our lagged *Var* on the corresponding β_{liq}, β_{ret}, the corresponding lagged ILMs together with other controls used in step 1. We use the residuals from these regressions as a measure of idiosyncratic liquidity risk, free from β_{liq}, β_{ret}, liquidity level effect, default risks, and other factors.

Finally, we run cross-sectional regressions of bond yields spreads on each of these residual components every quarter from 2004:Q1 to 2008:Q2 and report their Fama-French coefficient estimates together with their robust *t*-statistics in Table IX. We find statistically significant impact of the residual liquidity level across three different measures of liquidity. Both the systematic liquidity risk measures load significantly positive for two out of three liquidity measures. Combined together, systematic risk measures do seem to have power beyond the liquidity level, default risks, and other factors to explain variations in bond spreads. Interestingly, the idiosyncratic component also shows an ability to explain the yield spreads when the Amihud and the Dispersion measures are used.

[Table IX should be placed here.]

We examine the economic magnitude of the impact of liquidity level, liquidity risk and idiosyncratic liquidity risk in a similar fashion as Dick-Nielsen et al. (2009). Every quarter, we rank the component of the yield spread predicted by the above four residual variables and compute the difference between the bottom 10th percentile and the top 10th percentile value, i.e., the relevant yield liquidity premium. For each quarter, these yield liquidity premiums are averaged across the three ILMs. In the graphs presented in Figure 3, starting from the first calendar quarter in 2004 to the last calendar quarter in 2008, we plot the premiums due to the residual liquidity level (labeled *Level)*, the residual systematic liquidity risk (the sum of the β_{liq} and β_{ret} components) (labeled *Market Risk*) and the idiosyncratic liquidity risk (labeled *Residual Risk*).

We find the (residual) premiums due to liquidity level and liquidity risk are quite comparable in magnitude. This suggests liquidity risk may be at least as important as liquidity level in explaining bond spreads. This result is not new in the equity literature since Acharya and Pedersen (2005) but, to our knowledge, it has not been documented for bond markets. In addition, we find sharp increases in both the liquidity level and risk premiums over the sample period. The liquidity level component jumps from about 20bps at the end of 2007 to about 70bps at the end of 2008. Similarly, the market risk component jumps from about 10bps to almost 50bps. When we combine the liquidity level and the systematic liquidity components, they show a premium of roughly 20 basis points in the first half of the sample, which goes up to 120 basis points by the last quarter. Stacking the idiosyncratic component on top of this graph hardly changes its pattern over time or its level, suggesting that the impact of the idiosyncratic component, though statistically significant, may not matter economically.

V. Concluding Remarks

We propose a new class of implied liquidity measures (ILMs) for bonds with or without transaction data. The ILMs belong to a broad family of non-transaction based liquidity measures first developed by Mahanti et al. (2008), computed by aggregating a bond's owners' liquidity preferences. While Mahanti et al. (2008) use investors' turnover ratios, we propose to use the average liquidity of investors' bond holdings as a revealed measure of investors' liquidity preferences.

Our approach offers several advantages. First, since the liquidity of a bond is measured using transactions by *all* investors, our measure, unlike the turnover ratio, is less subject to cash management practices of institutional investors. Second, we rely only on publicly available data. Third, we show that ILMs are robust measures of liquidity, both in time series and cross-section and are strongly priced in bond spreads. Fourth, the ILMs can be calibrated to the monthly, or even weekly, frequency. This allows us to explicitly quantify a bond's systematic liquidity risk in the sense of Acharya and Pedersen (2005). We document that systematic liquidity risks have a significant effect on bond spreads, incremental to that of the liquidity level, and that both effects dramatically increase following the onset of the financial crisis.

From a bird's-eye view, we are able to wed the clever idea of Mahanti et al. (2008) in utilizing the holdings structure of institutional investors to circumvent the lack of transaction data in the bond market with the advances in the micro-structure literature which has developed transactions-based liquidity measures. Relative to the transaction-based approaches, we offer a much broader coverage of bonds. Relative to the latent measure by Mahanti et al. (2008), thanks to the use of other well-developed liquidity measures in gauging investors' liquidity preferences as well as the wealth of transaction data made available recently by the TRACE database, we provide an empirically robust measure of liquidity level that requires only publicly available data. The power of the ILMs is obtained by synergizing multiple approaches to measuring liquidity and multiple datasets which have so far only been used separately.

The lack of a reliable bond liquidity measure, conveniently implementable to a broad cross-section of particularly illiquid bonds, has so far denied us in-depth investigations of bond liquidity in rather illiquid segments of the bond markets – supposedly exactly where liquidity matters the most. For example, the connection between a firm's transparency and the liquidity of its bonds is important and potentially of interest to practitioners and researchers alike but the exact quantification of this linkage has not been easy. This is one of the topics we are currently exploring, using the ILMs proposed in this paper.

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Figure 1: Cross-sectional Correlation among Liquidity Measures over Time

This figure reports cross-sectional correlations among liquidity measures every year from 2003 to 2008 with the years, in increasing order, represented by columns running from left (dark grey) to right (light grey). The liquidity measures included are Amihud, Roll and Dispersion and their corresponding implied (I-) versions. The Amihud measure is the calendar-year average of $|R_t|/Daily\ Trading\ Volume$ where R_t is bonds' daily return and trading volume is in millions of dollars. The Roll measure is $2\sqrt{-\mathrm{cov}(R_{t-1},R_t)}$, computed over each year in the sample. The Dispersion measure is the calendar-year average of $(P_{max,t} - P_{min,t})/P_{last,t}$ where $P_{max,t}$, $P_{min,t}$, $P_{last,t}$ are the daily maximal, minimal and last trading prices, respectively. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over each quarter. The implied measure of a given bond is then computed as the weighted average of its owners' quarterly liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

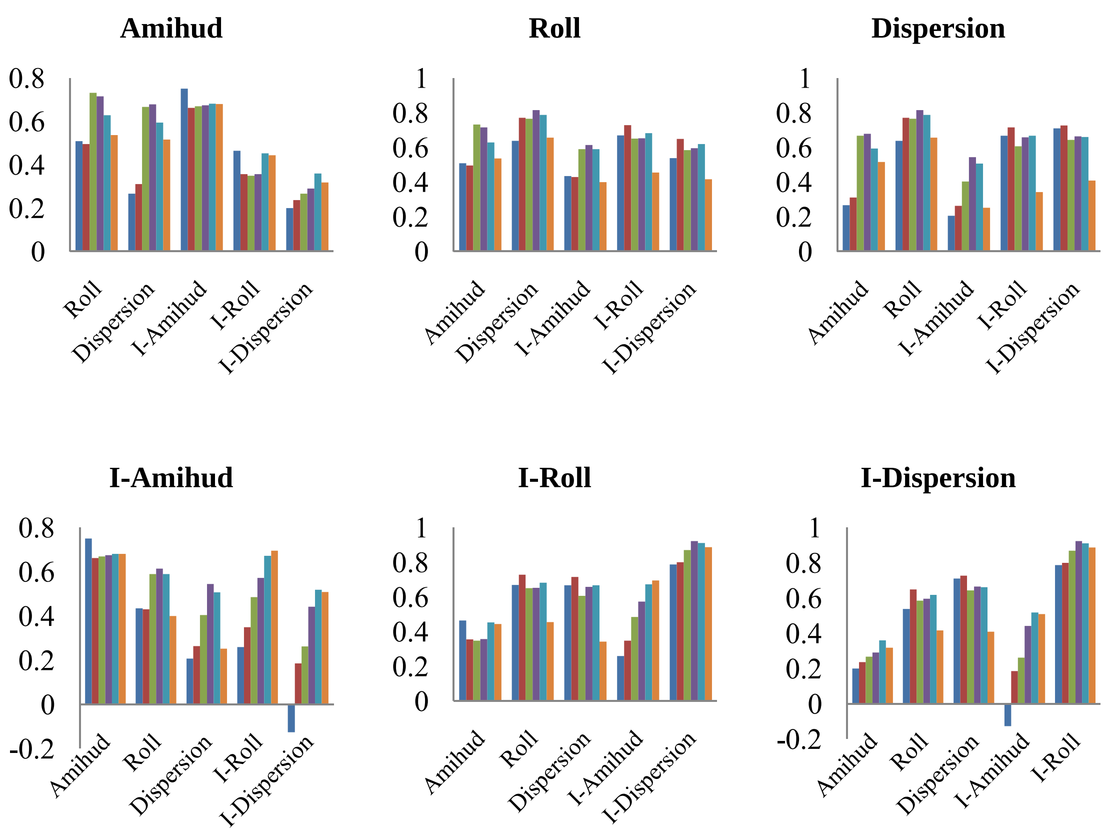


Figure 2: Price, Quantity and Yield Premium of Residual Liquidity

Prices of residual liquidity are obtained as quarterly coefficient estimates in cross-sectional regressions of quarterly average yield spreads of non-callable bonds on (one-quarter-) lagged implied liquidity measures orthogonalized on: the current quarter 5-year CDS spread, recovery rate, term structure level, curvature, slope factors, industry, ratings and other bonds fixed effects. These orthogonalized components of liquidity are then sorted in increasing order every quarter. The difference between the bottom 10th percentile value and the top 10th percentile value is computed as the *quantity* of residual liquidity. The product of price and quantity gives the *yield premium* of residual liquidity. The implied liquidity measures used are based on the Amihud, Roll, and Dispersion measures of liquidity. The Amihud measure is the calendar-year average of $|R_t|$*/Daily Trading Volume* where R_t is bonds' daily return and trading volume is in millions of dollars. The Roll measure is $2\sqrt{-\text{cov}(R_{t-1}, R_t)}$, computed over each year in the sample. The Dispersion measure is the calendar-year average of $(P_{max,t} - P_{min,t})/P_{last,t}$ where $P_{max,t}$, $P_{min,t}$, $P_{last,t}$ are the daily maximal, minimal and last trading prices, respectively. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over each quarter. The implied measure of a given bond is then computed as the weighted average of its owners' quarterly liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

Panel A: I-Amihud Measure

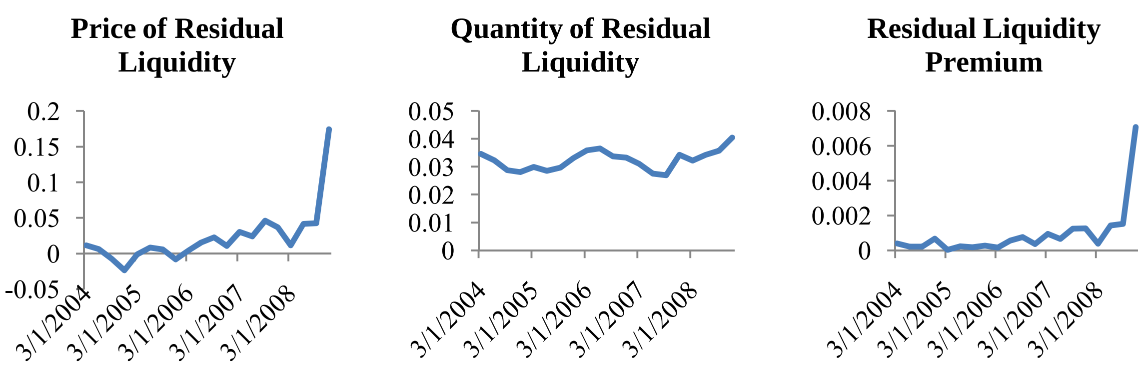
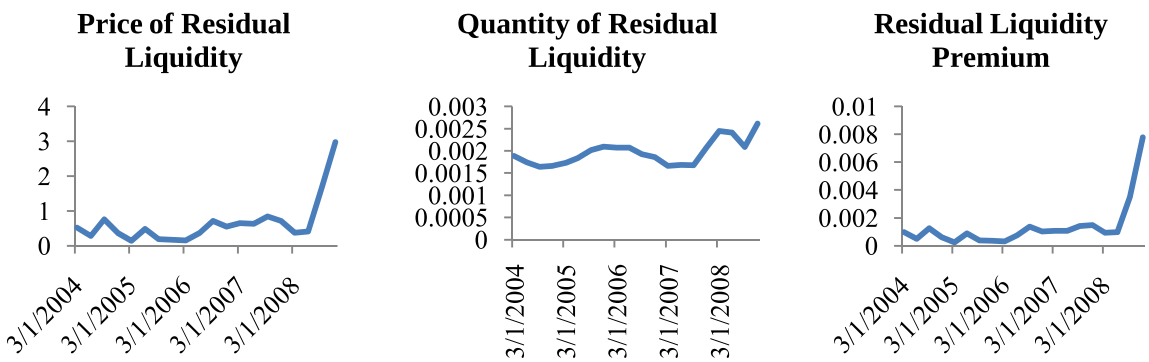


Figure 2: Price, Quantity and Yield Premium of Residual Liquidity (continued)

Panel B: I-Roll Measure



Panel C: I-Dispersion Measure

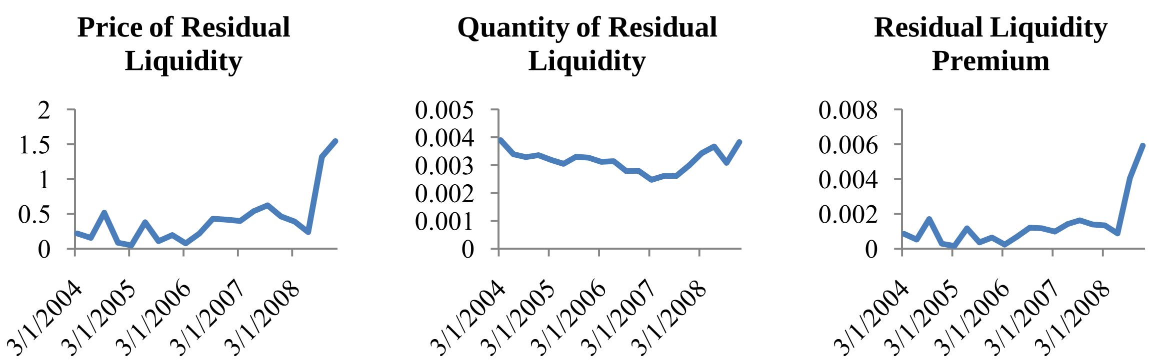


Figure 3: Yield Liquidity Premiums of Residual Components of Liquidity Level, Liquidity Market Risks and Liquidity Idiosyncratic Risks

Yield liquidity premiums are obtained by first regressing average quarterly yield spreads of non-callable bonds on (1) (one-quarter-) lagged implied liquidity measures (I-measure); (2) the 24-month covariance between changes in I-measures and changes in market-level of liquidity (β_{liq}); (3) the 24-month covariance between changes in I-measures and bond-market's returns (β_{ret}); and (4) the 24-month variance of changes in the I-measures. (2), (3), and (4) are scaled by the variance of bond market's returns over the same time window. All four variables are residual in the sense that they are orthogonalized against credit risk controls, current market conditions, and industry, ratings and bonds fixed effects. Additionally, (2) is also orthoganalized against (1); (3) against (1) and (2); (4) against (1), (2), and (3). Cross-sectional regressions are run every quarter from 2004:Q1 to 2008:Q4. The component of yield spread predicted by (1), (2), (3), and (4) is ranked every quarter with the resulting difference between the bottom 10th percentile and the top 10th percentile value being the relevant yield liquidity premium. For each quarter, these yield liquidity premiums are averaged across the three I-measures. In the graphs below, the *Level* corresponds to the I-measure component. *Market Risk* correspondes to the sum of the β_{liq} and β_{ret} components. *Residual Risk* corresponds to variance of changes in the I-measure component. Bonds' fixed effects controls include Coupon, Age, Maturity, and bond's original Issue Size (logged). Credit risk controls include the contemporaneous 5-year CDS spreads and their associated recovery rate. Economic conditions are controlled for by including the level, curvature and slope factors of the term structure of interest rates. Industry fixed effects and ratings fixed effects together with pre-tax coverage dummies are included in all regressions. The implied liquidity measures used are based on the Amihud, Roll, and Dispersion measures of liquidity. The Amihud measure, the Roll measure and the Dispersion measure and their implied versions are defined in Figure 2. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

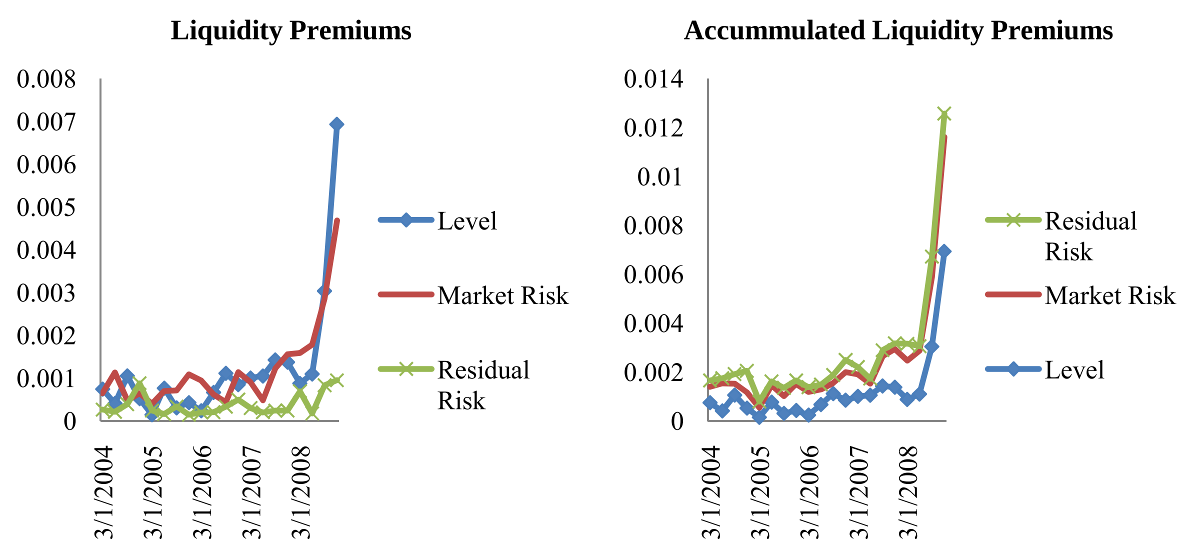


Table I: Bond Investors' Coverage

This table reports descriptive statistics of bonds' ownership coverage by year. Panel A and B report the extent of ownership (fraction of original issue size) and the number of owners, covered by insurance companies and mutual funds whose bonds' holdings are obtained from NAIC and MD, respectively. Panel C reports the number of bonds owned by an investing institution covered by either NAIC or MD. Liquidity is measured using the Amihud, Roll and Dispersion measures. The Amihud measure is the calendar-year average of $|R_t|$/*Daily Trading Volume* where R_t is bonds' daily return and trading volume is in millions of dollars. The Roll measure is $2\sqrt{-\operatorname{cov}(R_{t-1}, R_t)}$, computed over each year in the sample. The Dispersion measure is the calendar-year average of $(P_{max,t} - P_{min,t})/P_{last,t}$ where $P_{max,t}$, $P_{min,t}$, $P_{last,t}$ are the daily maximal, minimal and last trading prices, respectively.

Panel A: Ownership Coverage (Fraction of Original Issue Size) at Bond Issue's Level

Year	Mean	10^{th} percentile	50^{th} percentile	90^{th} percentile	Standard Deviation
2003	40.9%	6.7%	40.2%	76.3%	25.4%
2004	41.4%	6.4%	40.2%	78.9%	26.4%
2005	40.6%	5.5%	39.6%	78.3%	26.8%
2006	38.8%	4.5%	37.1%	76.5%	26.6%
2007	38.0%	4.8%	36.4%	74.5%	26.0%
2008	38.6%	5.3%	37.1%	74.9%	25.7%

Panel B: Ownership Coverage (Number of Owners) at Bond Issue's Level

Year	Mean	10^{th} percentile	50^{th} percentile	90^{th} percentile	Standard Deviation
2003	42.5	6	28	95	46.2
2004	42.9	6	29	96	45.6
2005	42.6	6	28	96	45.3
2006	41.8	6	27	95	44.8
2007	43.7	6	29	98	46.1
2008	48.4	7	32	108	49.8

Panel C: Number of Bonds Owned at Investors' Level

Year	Mean	10^{th} percentile	50^{th} percentile	90^{th} percentile	Standard Deviation
2003	66.7	4	27	170	116.4
2004	67.5	4	28	168	121.7
2005	64.2	3	27	153	118.1
2006	64.1	3	26	150	120.4
2007	65.0	3	27	146	125.3
2008	60.8	3	25	139	118.0

Table II: Measurability of Liquidity Measures

This table reports the number of bond issue – year combinations covered by each of the Amihud, Roll, Dispersion liquidity measures and their corresponding implied (I-) versions. *Panel A* reports the coverage by years. *Panel B* reports the coverage by bond age. *Panel C* reports the coverage by bond maturity. *Panel D* reports the coverage by bond rating groups. The Amihud measure is the calendar-year average of $|R_t|$*/Daily Trading Volume* where R_t is bonds' daily return and trading volume is in millions of dollars. The Roll measure is $2\sqrt{-\text{cov}(R_{t-1}, R_t)}$, computed over each year in the sample. The Dispersion measure is the calendar-year average of $(P_{max,t} - P_{min,t})/P_{last,t}$ where $P_{max,t}$, $P_{min,t}$, $P_{last,t}$ are the daily maximal, minimal and last trading prices, respectively. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over each quarter. The implied measure of a given bond is then computed as the weighted average of its owners' quarterly liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

Panel A: Bond Coverage by Year

	2003	2004	2005	2006	2007	2008
Amihud	1388	2058	3571	3329	2881	2737
Roll	1102	1530	2543	2337	1961	1916
Dispersion	924	1260	2191	1992	1737	1983
I-Amihud	7326	7754	7655	7622	7575	6980
I-Roll	7284	7723	7633	7599	7538	6953
I-Dispersion	7318	7750	7653	7617	7564	6974

Panel B: Bond Coverage by Age

	Less than 2 years	Between 2 and 5 years	Greater than 5 years
Amihud	2382	7391	6191
Roll	1727	5298	4364
Dispersion	1550	4702	3835
I-Amihud	8195	16143	19102
I-Roll	8148	16058	19070
I-Dispersion	8185	16128	19096

Table II: Measurability of Liquidity Measures (continued)

Panel C: Bond Coverage by Maturity

	Less than 5 years	Between 5 and 10 years	Between 10 and 20 years	Greater than 20 years
Amihud	6997	5087	2091	1789
Roll	5133	3751	1338	1167
Dispersion	4517	3280	1227	1063
I-Amihud	18423	15746	5954	4789
I-Roll	18324	15699	5926	4781
I-Dispersion	18401	15741	5947	4787

Panel D: Bond Coverage by Rating

	AA- to AAA	BBB- to A+	D to BB+
Amihud	2884	8217	3257
Roll	2156	5905	2189
Dispersion	1980	5080	2036
I-Amihud	7466	17562	5531
I-Roll	7423	17556	5523
I-Dispersion	7463	17560	5529

Table III: Correlation between Liquidity Measures and Other Variables

This table reports correlation statistics between liquidity measures and other variables. The liquidity measures included are Amihud, Roll and Dispersion and their corresponding implied (I-) versions. *Panel A* reports the average yearly cross-sectional correlations among the liquidity measures. *Panel B* reports the cross-sectional median of the time-series correlations among the liquidity measures. *Panel C* reports the average yearly cross-sectional correlations between the liquidity measures and bonds' fixed effects including coupon, maturity, age and (logged) original issue size. *Panel D* reports the average yearly cross-sectional correlations between the liquidity measures and bond returns' volatility, equity return volatility, earnings forecast dispersions and the frequency of zero returns, all computed over calendar-year windows. Earnings forecasts are obtained from the First Call dataset. The Amihud measure, the Roll measure and the Dispersion measure are defined in Table II. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over each quarter. The implied measure of a given bond is then computed as the weighted average of its owners' quarterly liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Transactions data are obtained from the FISD and TRACE.

Panel A: Average Yearly Cross-Sectional Correlations between Liquidity Measures

	Amihud	Roll	Dispersion	I-Amihud	I-Roll	I-Dispersion
Amihud		0.6028	0.5054	0.6863	0.4036	0.2785
Roll	0.6028		0.7384	0.5094	0.6392	0.5667
Dispersion	0.5054	0.7384		0.3627	0.6092	0.6356
I-Amihud	0.6863	0.5094	0.3627		0.5054	0.2982
I-Roll	0.4036	0.6392	0.6092	0.5054		0.8624
I-Dispersion	0.2785	0.5667	0.6356	0.2982	0.8624	

Panel B: Median Time Series Correlations between Liquidity Measures

	Amihud	Roll	Dispersion	I-Amihud	I-Roll	I-Dispersion
Amihud		0.8521	0.7913	0.7763	0.7861	0.7483
Roll	0.8521		0.9559	0.8051	0.9497	0.9370
Dispersion	0.7913	0.9559		0.7397	0.9546	0.9554
I-Amihud	0.7763	0.8051	0.7397		0.4589	0.5458
I-Roll	0.7861	0.9497	0.9546	0.4589		0.9344
I-Dispersion	0.7483	0.9370	0.9554	0.5458	0.9344	

Table III: Correlation between Liquidity Measures and Other Variables (continued)

Panel C: Average Yearly Cross-Sectional Correlations between Liquidity Measures and Fixed Bond Effects

	Coupon	Maturity	Age	Issue Size
Amihud	0.0832	0.2608	0.1782	-0.7285
Roll	0.2030	0.3963	0.0947	-0.3767
Dispersion	0.2342	0.4353	0.0413	-0.2798
I-Amihud	0.2037	0.3957	0.3828	-0.3967
I-Roll	0.3325	0.4674	0.1176	-0.2195
I-Dispersion	0.2830	0.3882	0.0291	-0.1372

Panel D: Average Cross-sectional Correlations between Liquidity Measures and other Variables

	Bond Volatility	Equity Volatility	Earnings Forecast Dispersion	Zero Return Frequency
Amihud	0.6535	0.0078	-0.0432	-0.3077
Roll	0.8709	0.1657	0.0778	-0.4644
Dispersion	0.8593	0.2457	0.1383	-0.4529
I-Amihud	0.5140	-0.1216	-0.1705	-0.2574
I-Roll	0.6707	0.1500	-0.0448	-0.4569
I-Dispersion	0.6123	0.1754	0.0034	-0.4342

Table IV: Regressions of Raw Liquidity Measures on Implied Liquidity Measures

This table reports the coefficient estimates (Est) with robust t-statistics (Tval) and R-squared (Rsq) obtained when regressing cross-sectionally raw liquidity measures on implied liquidity measures. Control variables include bond fixed effects (coupon, maturity, age, (logged) original issue size), leverage ratio (long term debts/assets), equity volatility, earnings forecast dispersion, trades frequency, trading volume (as a fraction of original issue size), industry fixed effects and ratings fixed effects. For comparison, R-squared's for regressions without the implied liquidity measures (Rsq*) are also reported. The liquidity measures included are Amihud, Roll and Dispersion and their corresponding implied (I-) versions. The Amihud measure, the Roll measure and the Dispersion measure are defined in Table II. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over each quarter. The implied measure of a given bond is then computed as the weighted average of its owners' liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

	Amihud				Roll				Dispersion			
	Est	Tval	Rsq	Rsq*	Est	Tval	Rsq	Rsq*	Est	Tval	Rsq	Rsq*
I-Amihud												
2003	2.78	6.66	0.68	0.63	0.08	3.53	0.41	0.39	0.10	3.33	0.61	0.59
2004	2.75	7.09	0.51	0.45	0.13	5.14	0.42	0.37	0.15	3.69	0.60	0.57
2005	3.91	11.70	0.52	0.42	0.19	11.16	0.49	0.35	0.19	9.48	0.58	0.47
2006	4.01	12.19	0.51	0.39	0.18	12.18	0.53	0.40	0.21	12.71	0.72	0.57
2007	3.71	12.05	0.53	0.39	0.15	10.70	0.54	0.40	0.16	9.72	0.69	0.59
2008	3.78	10.49	0.55	0.44	0.18	6.48	0.27	0.19	0.11	4.37	0.57	0.53
I-Roll												
2003	39.84	5.59	0.67	0.64	3.01	9.01	0.51	0.38	4.55	9.78	0.73	0.59
2004	32.39	6.21	0.49	0.45	3.35	12.04	0.52	0.36	5.00	11.30	0.69	0.57
2005	52.79	9.32	0.52	0.45	3.29	11.94	0.53	0.34	3.39	11.24	0.60	0.45
2006	56.83	11.25	0.50	0.40	3.12	12.75	0.56	0.39	3.24	11.17	0.71	0.56
2007	58.54	10.29	0.51	0.41	3.13	12.27	0.56	0.38	3.20	9.73	0.72	0.58
2008	32.48	6.53	0.51	0.47	2.70	6.23	0.30	0.20	1.57	4.46	0.58	0.54
I-Dispersion												
2003	13.30	4.45	0.66	0.64	1.07	6.95	0.46	0.39	1.80	6.76	0.72	0.60
2004	13.56	4.83	0.48	0.46	1.60	10.55	0.50	0.38	2.71	10.87	0.69	0.57
2005	23.78	6.96	0.50	0.45	1.35	6.97	0.45	0.35	1.64	7.31	0.57	0.47
2006	28.53	9.03	0.48	0.42	1.52	8.97	0.51	0.40	1.64	8.24	0.66	0.57
2007	37.51	9.01	0.50	0.42	1.98	11.01	0.53	0.38	2.12	8.96	0.70	0.57
2008	20.83	5.28	0.49	0.47	2.07	5.92	0.28	0.20	1.41	5.93	0.59	0.54

Table V: Summary Statistics of Implied Liquidity and Liquidity Risk Measures

This table reports the cross-sectional mean, 25th (P25), 50th (P50), 75th (P75) percentile values and the standard deviations of implied measures of liquidity level (Liq) and liquidity risk (Var, β_{liq}, β_{ret}) as of December of 2004, 2006, and 2008. The three implied measures (Liq) correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. We compute the 24-month variance of Liq (Var), the 24-month covariance between Liq and market-level of liquidity (β_{liq}) and the 24-month covariance between Liq and bond-market's returns (β_{ret}), scaled by the variance of bond market's returns over the same time window. Market-level of liquidity and return are the cross-sectional simple averages of liquidity and bonds' returns, respectively, computed monthly. The Amihud measure, the Roll measure and the Dispersion measure are defined in Table II. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over the relevant time window (quarterly: to compute liquidity level, monthly: to compute liquidity risk). The implied measure of a given bond is then computed as the weighted average of its owners' liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of their quarterly counterparts.

	Amihud				Roll				Dispersion			
	Liq	Var	β_{liq}	β_{ret}	Liq	Var	β_{liq}	β_{ret}	Liq	Var	β_{liq}	β_{ret}
2004												
Mean	0.100	3.605	3.267	-0.734	0.012	0.023	0.016	-0.021	0.018	0.099	0.047	-0.047
P25	0.082	1.736	2.559	-0.785	0.011	0.018	0.015	-0.023	0.016	0.071	0.041	-0.052
P50	0.097	2.979	3.192	-0.643	0.012	0.021	0.016	-0.019	0.017	0.086	0.046	-0.043
P75	0.115	4.818	3.951	-0.591	0.013	0.026	0.018	-0.015	0.019	0.107	0.051	-0.035
Std	0.026	2.425	1.075	0.225	0.002	0.008	0.003	0.010	0.003	0.053	0.013	0.017
2006												
Mean	0.094	2.944	2.663	-1.247	0.011	0.014	0.016	-0.056	0.014	0.050	0.037	-0.107
P25	0.077	1.069	1.769	-1.468	0.010	0.007	0.013	-0.058	0.013	0.027	0.027	-0.106
P50	0.091	1.615	2.457	-1.071	0.011	0.010	0.015	-0.039	0.014	0.036	0.032	-0.076
P75	0.108	2.846	3.379	-0.903	0.012	0.015	0.018	-0.032	0.016	0.053	0.041	-0.063
Std	0.024	4.214	1.428	0.495	0.002	0.012	0.005	0.037	0.002	0.044	0.016	0.072
2008												
Mean	0.265	5.604	5.341	-0.815	0.038	0.114	0.111	-0.012	0.047	0.166	0.147	-0.031
P25	0.211	3.255	4.247	-0.978	0.034	0.094	0.102	-0.015	0.043	0.144	0.137	-0.046
P50	0.263	4.879	5.256	-0.652	0.037	0.111	0.111	-0.006	0.046	0.161	0.146	-0.023
P75	0.315	7.160	6.374	-0.442	0.040	0.127	0.119	-0.001	0.049	0.180	0.154	-0.014
Std	0.078	3.436	1.611	0.516	0.006	0.032	0.015	0.018	0.007	0.038	0.016	0.024

Table VI: Regression of Yield Spreads on Liquidity Level

This table reports the Fama-MacBeth regression estimates (Est) together with robust t-statistics (Tval) when regressing average quarterly yield spreads of non-callable bonds on (one-quarter) lagged implied liquidity measures (I-measure). Cross-sectional regressions are run every quarter from 2004:Q1 to 2008:Q2. Coefficient estimates are then averaged over time. Bonds' fixed effects controls include Coupon, Age, Maturity, and bond's original Issue Size (logged). Credit risk controls include Vassalou and Xing (2004)'s risk-neutral distance to default and tangibility (Property, Plant and Equipment scaled by Total Assets) in Panel A, and contemporaneous 5-year CDS spread and its associated recovery rate in Panel B. Economic conditions are controlled for by including the level, curvature and slope factors of the term structure of interest rates. Industry fixed effects and ratings fixed effects together with pre-tax coverage dummies are included in all regressions. The implied liquidity measures used are based on the Amihud, Roll, and Dispersion measures of liquidity. The Amihud measure, the Roll measure and the Dispersion measure are defined in Table II. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over each quarter. The implied measure of a given bond is then computed as the weighted average of its owners' quarterly liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. We use a 4-quarter moving average of the implied measures in the regressions. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

Panel A: Risk-neutral Distance to Default as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-measure	0.0116	1.81	1.0486	13.85	0.8180	12.31
Coupon	0.0009	6.75	0.0007	6.21	0.0006	5.87
Age	-0.0001	-4.08	-0.0001	-4.56	-0.0001	-3.73
Maturity	0.0001	3.95	0.0000	1.23	0.0000	0.53
Issue size	-0.0020	-9.34	-0.0019	-7.03	-0.0019	-7.52
Distance to default	0.1220	5.81	0.1122	5.84	0.1039	5.89
Tangibility	0.0003	0.60	0.0010	1.75	0.0010	1.92
Level factor	-0.0016	-0.54	-0.0010	-0.33	-0.0003	-0.09
Curvature factor	0.0066	1.29	0.0062	1.37	0.0062	1.39
Slope factor	0.0035	1.46	0.0030	1.41	0.0019	0.95
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.6376		0.6326		0.6321	

Table VI: Regression of Yield Spreads on Liquidity Level (continued)

Panel B: Contemporaneous 5-year CDS spreads as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-measure	0.0109	2.82	0.4310	9.37	0.2921	7.64
Coupon	0.0007	7.49	0.0006	7.04	0.0006	7.05
Age	-0.0001	-2.88	0.0000	-2.05	0.0000	-1.70
Maturity	0.0001	3.15	0.0001	2.43	0.0001	2.47
Issue size	-0.0012	-12.96	-0.0012	-13.97	-0.0012	-14.70
CDS spread	0.0068	33.14	0.0068	31.11	0.0067	30.18
Recovery	0.0073	1.53	0.0076	1.66	0.0076	1.65
Level factor	-0.0005	-0.14	0.0001	0.02	-0.0003	-0.08
Curvature factor	0.0088	1.96	0.0098	2.31	0.0084	1.92
Slope factor	0.0042	1.79	0.0044	1.87	0.0043	1.82
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.7223		0.7178		0.7144	

Table VII: Regressions of Yields Spreads on Systematic Liquidity Risks

This table reports the Fama-MacBeth regression estimates (Est) together with robust t-statistics (Tval) when regressing average quarterly yield spreads of non-callable bonds on (one-quarter) lagged implied liquidity measures (I-measure) together with (1) the 24-month covariance between changes in I-measures and changes in market-level of liquidity (β_{liq}) in Panels A and B; or (2) the 24-month covariance between changes in I-measures and bond-market's returns (β_{ret}) in Panels C and D. Both (1) and (2) are scaled by variance of bond market's returns over the same time window. Cross-sectional regressions are run every quarter from 2004:Q1 to 2008:Q2. Coefficient estimates are then averaged over time. Bonds' fixed effects controls include Coupon, Age, Maturity, and bond's original Issue Size (logged). Credit risk controls include Vassalou and Xing (2004)'s risk-neutral distance to default and tangibility (Property, Plant and Equipment scaled by Total Assets) in Panels A and C, and contemporaneous 5-year CDS spreads and their associated recovery rate in Panels B and D. Economic conditions are controlled for by including the level, curvature and slope factors of the term structure of interest rates. Industry fixed effects and ratings fixed effects together with pre-tax coverage dummies are included in all regressions. The implied liquidity measures used are based on the Amihud, Roll, and Dispersion measures of liquidity. The Amihud measure, the Roll measure and the Dispersion measure are defined in Table II. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over the relevant time window (quarterly: to compute liquidity level, monthly: to compute liquidity risk). The implied measure of a given bond is then computed as the weighted average of its owners' liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. We use a 4-quarter moving average of the implied measures in the regressions. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

Panel A: β_{liq} as Regressor, Risk-neutral Distance to Default as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-Measure	0.0158	1.70	1.1203	7.84	0.5861	8.54
Liquidity Risk (β_{liq})	0.0005	1.02	0.4595	3.12	0.6147	3.56
Coupon	0.0007	5.39	0.0006	4.97	0.0005	4.44
Age	-0.0001	-2.98	-0.0001	-3.21	-0.0001	-2.20
Maturity	0.0001	3.96	0.0000	0.47	0.0000	0.52
Issue size	-0.0020	-8.47	-0.0019	-6.94	-0.0019	-7.85
Distance to default	0.1181	5.75	0.1104	5.59	0.1032	5.68
Tangibility	-0.0001	-0.22	0.0005	0.94	0.0009	1.72
Level factor	0.0006	0.21	0.0005	0.18	0.0016	0.52
Curvature factor	0.0060	1.25	0.0055	1.20	0.0068	1.41
Slope factor	0.0012	0.49	0.0015	0.71	0.0000	0.00
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.6336		0.631		0.6306	

Table VII: Regressions of Yields Spreads on Systematic Liquidity Risks (continued)

Panel B: β_{liq} as Regressor, Current 5-year CDS spreads as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-measure	0.0145	2.64	0.4033	4.90	0.1734	3.64
Liquidity Risk (β_{liq})	0.0005	1.65	0.2466	3.81	0.2449	4.81
Coupon	0.0006	6.95	0.0005	5.66	0.0005	5.74
Age	0.0000	-2.25	0.0000	-1.47	0.0000	-0.35
Maturity	0.0001	2.87	0.0001	2.13	0.0001	2.56
Issue size	-0.0012	-12.82	-0.0012	-14.55	-0.0013	-14.34
CDS spread	0.0068	32.97	0.0066	29.02	0.0066	26.01
Recovery	0.0068	1.53	0.0068	1.65	0.0061	1.58
Level factor	0.0010	0.32	0.0018	0.56	0.0008	0.25
Curvature factor	0.0104	2.19	0.0101	2.07	0.0092	1.96
Slope factor	0.0031	1.09	0.0041	1.59	0.0038	1.52
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.7097		0.7064		0.6998	

Panel C: β_{ret} as Regressor, Distance to Default as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-Measure	0.0238	3.79	1.2134	9.31	0.9174	6.89
Liquidity Risk (β_{ret})	0.0003	0.25	0.0273	3.44	0.0328	4.14
Coupon	0.0007	5.02	0.0006	4.64	0.0006	4.56
Age	-0.0001	-3.17	-0.0001	-3.30	-0.0001	-2.74
Maturity	0.0001	3.32	0.0000	0.59	0.0000	0.01
Issue size	-0.0020	-8.96	-0.0019	-7.55	-0.0019	-8.15
Distance to default	0.1172	5.56	0.1094	5.93	0.1056	5.44
Tangibility	0.0001	0.18	0.0005	0.95	0.0009	1.67
Level factor	0.0015	0.54	0.0014	0.43	0.0020	0.63
Curvature factor	0.0074	1.44	0.0070	1.60	0.0062	1.56
Slope factor	0.0021	0.89	0.0018	0.74	0.0004	0.18
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.6323		0.6284		0.6305	

Table VII: Regressions of Yields Spreads on Systematic Liquidity Risks (continued)

Panel D: β_{ret} as Regressor, Current 5-year CDS spreads as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-measure	0.0155	3.72	0.5007	7.26	0.3018	5.95
Liquidity Risk (β_{ret})	0.0007	2.62	0.0236	3.89	0.0173	2.84
Coupon	0.0006	6.86	0.0005	6.01	0.0005	5.86
Age	-0.0001	-2.68	0.0000	-2.07	0.0000	-0.97
Maturity	0.0001	2.76	0.0001	2.22	0.0001	2.23
Issue size	-0.0012	-12.98	-0.0013	-13.98	-0.0013	-14.35
CDS spread	0.0068	31.30	0.0067	29.68	0.0066	27.64
Recovery	0.0067	1.52	0.0062	1.51	0.0066	1.58
Level factor	0.0013	0.40	0.0014	0.48	0.0010	0.32
Curvature factor	0.0090	1.83	0.0107	2.56	0.0090	2.06
Slope factor	0.0041	1.60	0.0047	1.65	0.0032	1.25
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.7092		0.7074		0.7025	

Table VIII: Regressions of Yields Spreads on Total Liquidity Risks

This table reports the Fama-MacBeth regression estimates (Est) together with robust t-statistics (Tval) when regressing average quarterly yield spreads of non-callable bonds on (one-quarter) lagged implied liquidity measures (I-measure) together with the 24-month variance of changes in I-measures (Total Liquidity Risk), scaled by variance of bond market's returns over the same time window. Cross-sectional regressions are run every quarter from 2004:Q1 to 2008:Q2. Coefficient estimates are then averaged over time. Bonds' fixed effects controls include Coupon, Age, Maturity, and bond's original Issue Size (logged). Credit risk controls include Vassalou and Xing (2004)'s risk-neutral distance to default and tangibility (Property, Plant and Equipment scaled by Total Assets) in Panel A, and contemporaneous 5-year CDS spreads and their associated recovery rate in Panel B. Economic conditions are controlled for by including the level, curvature and slope factors of the term structure of interest rates. Industry fixed effects and ratings fixed effects together with pre-tax coverage dummies are included in all regressions. The implied liquidity measures used are based on the Amihud, Roll, and Dispersion measures of liquidity. The Amihud measure, the Roll measure and the Dispersion measure are defined in Table II. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over the relevant time window (quarterly: to compute liquidity level, monthly: to compute liquidity risk). The implied measure of a given bond is then computed as the weighted average of its owners' liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. We use a 4-quarter moving average of the implied measures in the regressions. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

Panel A: Risk-neutral Distance to Default as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-Measure	0.0025	0.37	1.1325	11.70	0.6921	10.91
Total Liquidity Risk	3.0871	4.06	735.71	2.30	1139.1	3.16
Coupon	0.0008	5.73	0.0006	5.29	0.0004	4.46
Age	-0.0001	-3.24	-0.0001	-3.19	0.0000	-1.26
Maturity	0.0001	4.13	0.0000	0.51	0.0000	0.30
Issue size	-0.0020	-8.81	-0.0018	-7.40	-0.0019	-8.05
Distance to default	0.1196	5.89	0.1089	5.90	0.1000	5.85
Tangibility	0.0000	0.00	0.0006	1.21	0.0011	2.22
Level factor	0.0005	0.16	0.0010	0.32	0.0015	0.50
Curvature factor	0.0070	1.36	0.0065	1.43	0.0059	1.35
Slope factor	0.0020	0.84	0.0008	0.33	0.0003	0.14
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.6350		0.6274		0.6363	

Table VIII: Regressions of Yields Spreads on Total Liquidity Risks (continued)

Panel B: Current 5-year CDS spreads as Credit Risk Controls

	Amihud		Roll		Dispersion	
	Est	Tval	Est	Tval	Est	Tval
I-measure	0.0110	1.77	0.4470	6.18	0.1630	3.18
Total Liquidity Risk	0.9292	1.74	359.57	2.50	678.03	3.63
Coupon	0.0006	6.75	0.0006	6.27	0.0005	6.25
Age	-0.0001	-2.69	0.0000	-1.79	0.0000	-0.05
Maturity	0.0001	2.88	0.0001	2.11	0.0001	2.62
Issue size	-0.0013	-12.72	-0.0012	-14.69	-0.0013	-14.77
CDS spread	0.0068	30.51	0.0066	27.01	0.0065	26.27
Recovery	0.0071	1.64	0.0070	1.68	0.0076	1.68
Level factor	0.0009	0.28	0.0012	0.41	0.0006	0.19
Curvature factor	0.0107	2.21	0.0103	2.27	0.0084	1.81
Slope factor	0.0037	1.34	0.0041	1.67	0.0037	1.49
Ratings FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Pre-tax coverage dummies	Yes		Yes		Yes	
Average Adjusted Rsquared	0.7079		0.7048		0.7043	

Table IX: Regressions of Yields Spreads on Residual Components of Liquidity Level, Liquidity Market Risks and Liquidity Idiosyncratic Risks

This table reports the Fama-MacBeth regression estimates (Est) together with robust t-statistics (Tval) when regressing average quarterly yield spreads of non-callable bonds on (1) (one-quarter-) lagged implied liquidity measures (I-measure); (2) the 24-month covariance between changes in I-measures and changes in market-level of liquidity (β_{liq}); (3) the 24-month covariance between changes in I-measures and bond-market's returns (β_{ret}); and (4) the 24-month variance of changes in the I-measures. (2), (3), and (4) are scaled by the variance of bond market's returns over the same time window. All four variables are residual in the sense that they are orthogonalized against bond fixed effects, credit risks controls, current market conditions, and industry and ratings fixed effects. Additionally, (2) is also orthoganalized against (1); (3) against (1) and (2); (4) against (1), (2), and (3). Cross-sectional regressions are run every quarter from 2004:Q1 to 2008:Q2. Coefficient estimates are then averaged over time. We do not report coefficient estimates of the control variables. Bonds' fixed effects controls include Coupon, Age, Maturity, and bond's original Issue Size (logged). Credit risk controls include the contemporaneous 5-year CDS spreads and their associated recovery rate. Economic conditions are controlled for by including the level, curvature and slope factors of the term structure of interest rates. Industry fixed effects and ratings fixed effects together with pre-tax coverage dummies are included in all regressions. The implied liquidity measures used are based on the Amihud, Roll, and Dispersion measures of liquidity The Amihud measure is the average of $|R_t|$/*Daily Trading Volume* where R_t is bonds' daily return and trading volume is in millions of dollars. The Roll measure is $2\sqrt{-\text{cov}(R_{t-1},R_t)}$. The Dispersion measure is the average of $(P_{max,t} - P_{min,t})/P_{last,t}$ where $P_{max,t}$, $P_{min,t}$, $P_{last,t}$ are the daily maximal, minimal and last trading prices, respectively. To compute the implied measures, we first compute the average liquidity level of each bond investor's portfolio over the relevant time window (quarterly: to compute liquidity level, monthly: to compute liquidity risk). The implied measure of a given bond is then computed as the weighted average of its owners' liquidity level with the weights being the natural logarithm of each owner's holding (in terms of fair value) of the bond. We use a 4-quarter moving average of the implied measures in the regressions. The three implied measures correspond to three different methods (Amihud, Roll, Dispersion) of measuring liquidity at the portfolio level. The yearly implied measures are simple averages of the corresponding implied measures computed quarterly. Bond investors holdings are obtained from the NAIC and Morningstar Direct. Bond transaction data are obtained from the Mergent FISD and TRACE databases.

	Amihud		Roll		Disp	
	Est	Tval	Est	Tval	Est	Tval
I-measure	0.0131	3.05	0.4617	8.75	0.3052	7.31
β_{liq}	0.0005	1.69	0.2721	4.10	0.2453	4.91
β_{ret}	0.0008	2.06	0.0276	4.54	0.0083	1.55
Liquidity Variance	1.3916	3.65	-76.879	-0.43	656.66	3.35