# Latent Liquidity: A New Measure of Liquidity, with an Application to Corporate Bonds

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#### Abstract

We present a new measure of liquidity known as "latent liquidity" and apply it to a unique corporate bond database. Latent liquidity is defined as the weighted average turnover of investors who hold a bond, where the weights are the fractional investor holdings. It can be used to measure liquidity in markets with sparse transactions data. This measure exhibits relationships with bond characteristics similar to those of other trade-based measures. For bonds that trade frequently, our measure has predictive power for both transaction costs and the price impact of trading, over and above trading activity and bond-specific characteristics thought to be related to liquidity.

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# 1 Introduction

An investor holding a security or considering the purchase of a security is exposed to liquidity, or, more precisely, the lack of it. The conventional "reduced-form" definition of liquidity is the gap between the fundamental value of a security and the price at which the security is actually transacted: high liquidity implies that this gap is small, and vice versa. In this paper, our goal is to understand the determinants of liquidity and its cross-sectional variability in the context of relatively illiquid markets. However, while liquidity is easy to define in theoretical terms, its empirical measurement in an accurate and reliable manner is quite difficult, except in markets that are relatively very liquid. This is because most commonly used metrics of liquidity rely on transactional information, such as volume and trading spreads, with relatively high frequency, which are unavailable when the asset in question is illiquid. For this reason, we first propose a measure for liquidity that does not require such transactions data. We call this measure latent liquidity, since it measures liquidity the way a typical "sell-side" dealer thinks about liquidity: it measures the accessibility of a security from sources where the security is currently being held. We apply this new measure of liquidity to try to understand the determinants of liquidity in one of the most well-known, but illiquid markets in the world - the market for U.S. corporate bonds. Additionally, for bonds that trade, we demonstrate that our measure has predictive power both for transaction costs and for the price impact of trading, over and above liquidity measures such as the trading volume, and bond specific characteristics such as age, amount outstanding, rating class and coupon.

The broad empirical issue of liquidity has been covered by many papers in both the equity and bond market literatures. In the equity markets, two key questions receiving a great deal of attention recently are first, whether liquidity differentials explain the cross-sectional variation in returns, and second, whether liquidity risk is priced.<sup>1</sup> Amihud and Mendelson (1986), Brennan and Subrah-

<sup>&</sup>lt;sup>1</sup>Liquidity risk is the uncertainty of how wide or narrow the gap between fundamental value and the transactions price of a security will be at any point in time. For all investors, current and potential, liquidity risk is a real risk that they bear, and hence may be "priced", if it has a systematic component. Every transaction is essentially a negative NPV project for the "buy-side" investor, because she is always transacting at a price worse than the security's fundamental value. However, if the investor knew how negative the NPV would be, then this would not be a risk - the investor could simply perform his asset allocation optimization by factoring in the transaction costs. The risk comes from not knowing how far off the investor will transact in relation to the fundamental value of the asset she is buying or selling.

manyam (1996), Brennan, Chordia and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998), Chordia, Roll, and Subrahmanyam (2000) find positive relationships between stock returns and overall liquidity as measured by spreads, depth, and volume. Meanwhile Chordia, Subrahmanyam and Anshuman (2001) find a negative relationship between liquidity and expected returns, while Hasbrouck and Seppi (2001) find no relationship. Finally, Huberman and Halka (2001), Pastor and Stambaugh (2003), Sadka (2004), and Bekaert, Harvey, and Lundblad (2005) examine the more relevant question of whether liquidity risk is a systematic factor.

Several authors have investigated measures of liquidity that do not rely on high-frequency data. Typically, these metrics rely only on daily volume and return data and can be related to Kyle's (1985) concept of the price impact of trading. Examples include the Amivest measure proposed by Amivest Capital Management, and the related Amihud (2002) measure, that are both based on absolute return and trading volume. The relationship between these measures (and their variants) and traditional microstructure-based measures is investigated by Hasbrouck (2005) who shows that the Amihud measure is a robust measure of price impact. Using this measure, Amihud (2002) shows there is an illiquidity premium in stock returns since the expected market illiquidity is correlated with stock excess return. Acharya and Pedersen (2005) also use this measure to investigate the various channels of the liquidity effect on stock returns in a unified liquidity-adjusted capital asset pricing model.

In the debt markets, much of the literature on liquidity has focused on the transactional characteristics of corporate debt. For example, Chakravarty and Sarkar (1999), Hong and Warga (2000), Schultz (2001), and Hotchkiss, Warga, and Jostava (2002) use the National Association of Insurance Commissioners (NAIC) database to study bid-ask spreads and trading volume in corporate bonds. Meanwhile Hotchkiss and Ronen (1999) and Alexander, Edwards, and Ferri (2000) use the Fixed Income Pricing System (FIPS) database of high-yield bonds, collected by the National Association of Securities Dealers (NASD) to study various aspects of liquidity and informational efficiency in the corporate bond market. Recently, there have been attempts to quantify transaction costs in the market. Bessembinder, Maxwell and Venkataraman (2005) use NAIC data in order to estimate round-trip transaction costs for a limited set of bonds using a signed-variable approach. Using the same data-set, Goldstein, Hotchkiss and Sirri (2005) establish that transaction costs have decreased after the introduction of centralized reporting of transactions by the National Association of Securities Dealers (NASD) in 2002.

The role of liquidity in the context of credit markets has been studied by several authors, who attempt to explain the yield spread on corporate bonds or credit default swaps. Several authors, including Duffee (1999), Duffie and Singleton (1997) Elton, Gruber, Agrawal and Mann (2001), Collin-Dufresne, Goldstein and Martin (2001), Houweling, Mentink, and Vorst (2003), Huang and Huang (2003), Perraudin and Taylor (2003), Chen, Lesmond, and Wei (2005), Edwards, Harris and Piwowar (2006), Eom, Helwege and Huang (2004), Liu, Longstaff and Mandell (2004), Longstaff, Mithal and Neis (2005), and De Jong and Driessen (2005) all present evidence of the non-default component of these spreads, and attribute at least part of it to illiquidity effects. However, in the absence of direct measures of liquidity for most corporate bonds, most researchers, so far, have been forced to rely on proxies such as age, notional amount oustanding, industry category, and credit risk. In the case of the most liquid bonds, some data on bid-ask spreads are used, but this approach is biased in favor of the most liquid bonds given the lack of trading in most US corporate bonds, as we document in detail below.<sup>2</sup> While these measures may be correlated with liquidity, it would be far better to obtain a more *direct* measure of liquidity, since these proxies for liquidity may be quite imperfect in the absence of frequent trading.

A common feature among all the empirical research on liquidity, irrespective of the markets studied, is that they use transactions data, such as trading volume and the bid-ask spread, to measure liquidity. This approach is feasible in markets that are reasonably liquid and have relatively continuous trading activity. However, this is not always a realistic option, in general, since the most interesting markets to study liquidity, or more precisely, the lack of it, are those where liquidity is a problem, i.e., in asset markets that lack liquidity, such as the real estate market, the art market, the corporate bond market, to name a few. In general, most assets in these markets do not trade regularly; hence transactions data are very sparse, for all but a handful of the assets in these markets, since there is no trading activity for the bulk of the assets for several consecutive months.

<sup>&</sup>lt;sup>2</sup>For example, Edwards, Harris and Piwowar (2006) show that of the  $70,000+$  corporate bonds outstanding in 2004, less than 17,000 experienced more than 9 trades that year.

Hence, conventional measures of liquidity such as the bid-ask spread and trade count are difficult to employ in these markets, except for the most liquid segment. Therefore, studies that use proxies of liquidity based on transactions data in these markets inevitably end up focusing on only the most liquid securities or markets - a classic case of looking for lost keys under the lamp post, where the light is shining, rather than where they were lost. Consequently, any results from such studies are skewed in the direction of the most liquid segment of these markets, and may not necessarily apply to the market as a whole. Clearly, what is needed, therefore, is a measure of liquidity that does not rely on transactions data; such a measure would be ideal for studying liquidity in markets where the issue is of greatest interest: those that are relatively illiquid.

In order to address the question of liquidity in relatively illiquid markets, we construct a new liquidity measure that estimates the accessibility of a security, rather than its trading characteristics, and apply this measure to the US corporate bond market. Our measure is simply the weighted average turnover of investors who hold a particular bond, where the weights are the fractional holdings of the amount outstanding of the bond.<sup>3</sup> Since corporate bonds trade in a dealer network, dealers rely on being able to access their "buy-side" clients' holdings either to purchase or sell bonds. If a bond is readily accessible, meaning a dealer can contact one of a number of "buy-side" clients and obtain the bond easily, the bond can be thought of as potentially liquid, even though it may not actually trade very much. Specifically, we conjecture that if a bond issue is held primarily by investors with high portfolio turnover, (e.g. a hedge fund) the bond may be thought of as more accessible - essentially, it is easier for a dealer to contact one of the investors holding this bond and convince them to sell it at a reasonable spread in relation to its fundamental value. On the other hand, if a bond issue is held primarily by investors with low portfolio turnover, such as long term buy-and-hold investors (e.g. insurance companies), it is more difficult for dealers to convince them to sell it, and hence, the bond is less accessible.

The theoretical underpinning for our proposed measure of liquidity is the insight offered by Amihud and Mendelson (1986) that in equilibrium, securities with higher transaction costs and poorer liquidity are held by investors with longer trading horizons, because they are able to amor-

<sup>&</sup>lt;sup>3</sup>We use the corporate bond market as an important example of an illiquid market, but it should be clear that the liquidity concepts and measures discussed here apply, more generally, to any security traded in an illiquid market.

tize their transaction costs over longer periods of time. In contrast to the exogenous treatment of transaction costs in Amihud and Mendelson (1986), Duffie, Garleanu and Pedersen(2003) endogenize transaction costs by presenting a search-based model of over-the-counter markets. They demonstrate that bid-ask spreads charged by market makers are likely to be higher when agents have lower trading frequencies, and hence fewer options to search. Vayanos and Wang (2005) present another search-based model to demonstrate that liquidity may get concentrated in some assets endogenously in equilibrium, leading to lower search times and lower transaction costs. These theoretical models may be seen as justifications for our measure of latent liquidity, which has the additional practical advantage that it does not require transactions data.

We investigate the drivers of this measure in the US corporate bond market.<sup>4</sup> We analyze various characteristics of a bond, such as its credit rating and maturity, to determine whether or not each characteristic contributes to higher or lower liquidity, or accessibility, for that bond. Since the corporate bond market is essentially an over-the-counter market, with a large number of dealers, obtaining data on this market is more difficult than for exchange-traded markets with a single locus of transactions. No single dealer has enough market share, and, therefore, handles enough transactions for a meaningful analysis to be conducted. For this reason, our data-set comes from the world's largest custody bank, which holds data from a large number of "buy-side" clients. As part of their custody process, these banks record the transactions conducted by their clients; thus, the largest custody banks essentially "see" across the transactions databases of multiple dealers. While not being able to access data on all the transactions in the corporate bond market, the largest custodians do record a substantial proportion of it. More importantly, the custodians become aware of only institutional, rather than inter-dealer, trading; thus, the database we use constitutes a more relevant portion of the trading universe (for the purpose of studying liquidity effects). As a result, the findings of the paper are much more appropriate for institutional trading and bond holdings.

In recent years, starting in mid-2002, the National Association of Securities Dealers (NASD)

<sup>&</sup>lt;sup>4</sup>Prior to the availability of transactions databases such as the NAIC or FIPS, studies typically employed yield spreads or issue size as proxies for liquidity. See, for example, Sarig and Warga (1989), Blume, Keim, and Patel (1991), and Crabbe and Turner (1995).

has initiated a program known as the Trade Reporting and Compliance Engine (TRACE), in which the individual members of the NASD report all their corporate bond transactions to a central agency. These transactions are aggregated into a common, market-wide database. However, the TRACE effort was not comprehensive in its initial years, although, as we find, it is becoming more so, with time. Furthermore, because the program is relatively new, a reasonably long history will not be available for many years. More importantly, as we shall see later, our measure of liquidity also requires information regarding the holdings of bonds by different investors. This is, clearly, not available in the TRACE database, which only records transactions volume and prices. In the context of this paper, however, we use transaction costs and price impacts estimated from TRACE data to validate our measure of latent liquidity.

In our empirical study, we find that credit quality, age, issue size, the original maturity value at issue date, and optionalities such as call, put, or convertibility, all have a strong impact on our measure of liquidity. In these regressions, we use three different measures of liquidity as a dependent variable: our latent liquidity measure and two transaction-based measures, which are all alternative formulations of trading volume and therefore available only for the relatively liquid segment of our sample. We observe that when we restrict ourselves to bonds in the liquid segment of our database that have a relatively high trading volume, the results from the regressions are similar whether we use latent liquidity or the transaction-based measures.

In order to validate our measure in the set of traded bonds, we also estimate transaction costs in the corporate bond market using a sub-sample of bonds for which trading volume is available in the TRACE database, using the limited dependent-variable model similar to Lesmond, Chen and Wei (2005). We demonstrate that latent liquidity has explanatory power for transaction costs, over and above observable bond characteristics such as coupon, rating, age and issue size, as well as realized trade count. Including latent liquidity eliminates the explanatory power of age and trade count for most quarters for which we are able to compute transactions costs. Unconditionally, there is a 200 basis point difference between the lowest ranked and the highest ranked bonds (by percentile of latent liquidity), and holding other variables constant, there is around a 105 basis point difference. As further validation that latent liquidity conveys incremental information, we compute the price impact of trading corporate bonds using the TRACE database, using the Amihud (2002) measure. We find that latent liquidity explains price impact both unconditionally, and over and above issue size, age, coupon, rating, and realized trade count. We find that, unconditionally, an increase in the latent liquidity percentile from 0 to 100% leads to an eight-fold decrease in the price impact, while conditionally, it leads to around a two-fold decrease in the price impact.

These results gives us some comfort that the latent liquidity statistic is a good proxy for liquidity. We receive additional confirmation for the validity of our measure from the results of similar empirical tests on the entire database (including the bonds that do not trade often enough for transaction-based liquidity measures to be calculated), where we find essentially the same results. From our empirical work, we conclude the following: when there is frequent trading and transactions data are available, our latent liquidity measure is as good, or better than transaction-based liquidity measures. When there is infrequent trading and transaction-based measures simply cannot be calculated, our latent liquidity measure still provides a proxy for the liquidity of a security.

This paper is organized as follows. Section 2 introduces the database we use and provides some indications of how representative it is of the market as a whole, in terms of both holdings and transactions. It also provides some statistics on the trading frequency of bonds in our sample. This section also discusses the composition of the database in terms of various bond characteristics, such as issue size, age, maturity, industry segment etc. Finally, the section concludes with a precise definition of latent liquidity, along with some graphs of the relationship between the proposed measure and key bond characteristics. In section 3, we present the results of a series of tests to check whether latent liquidity provides a good measure of liquidity. We present the results for the relationship between latent liquidity and the bond characteristics for both the liquid and the less liquid segment of our sample to provide a sense of how different these are are from the more liquid segment. We also relate the characteristics of bonds to both latent liquidity and two transactionbased measures of liquidity, for the most liquid segment of the market, where the latter measures can be constructed. Section 4 defines a measure of transaction costs using corporate bond trades reported on the TRACE system, and shows that even in the most actively traded bonds, latent liquidity has a greater explanatory power on transaction costs than either bond characteristics, or realized measures of liquidity. Section 5 shows that even for the most actively traded bonds, latent liquidity has a incremental explanatory power for price impact over and above bond characteristics or realized measures of liquidity. Section 6 concludes with a discussion of the implications of the proposed measure of liquidity for future research.

## 2 Liquidity Measurement and Data

While the corporate bond market appears to be an ideal market to study liquidity, particularly the drivers of liquidity, two primary reasons explain the lack of rigorous empirical research on liquidity in the US corporate bond market. First, the corporate bond market is a dealer market (essentially an over-the counter (OTC) market); hence, until recently, no central data source exists for all the transactions occurring in the market. This has been remedied partially by the establishment of the TRACE effort in mid-2002. Second, even after the establishment of the TRACE database, in the absence of transactions data for all but the most liquid bonds, we need an alternative metric of liquidity, such as latent liquidity, that does not rely on such data. (It should be noted that the TRACE database does not have information about the holdings or trading behavior of individual investors, which are required inputs for the computation of latent liquidity.)

#### 2.1 The US Corporate Bond Database

Since no single comprehensive source of trading data exists for the US corporate bond market as a whole, for a long enough period, one has to rely on data from a sub-set of the market. One could approach an individual dealer and collect and analyze the transactions in which that dealer participates. However, this approach leaves open the possibility of biases: for example, a particular dealer may be a market leader in the high-yield segment of the market, in which case the database the researcher puts together from that dealer's transactions will be biased towards high-yield bonds. In order to mitigate this problem, we use the databases of the world's largest securities custodian, State Street Corporation (SSC). The primary functions of a custodian are to provide trade clearance and settlement, the safekeeping of securities, and asset servicing such as dividend collection, proxy voting, and accounting and tax services. A custodian is not tied to any one dealer: its customers are the owners of assets, not the broker/dealers. Asset owners typically use multiple dealers to execute their transactions, but typically use one custodian for all their holdings. Since a custodian is not associated with any single dealer, its data aggregates transactions across multiple dealers. Therefore, the transactions database of a custodian, particularly the largest one, should be much more comprehensive than that of any one individual dealer; thus, the database is likely to be much more representative of the aggregate market, particularly relating to institutional investors. More importantly, unlike even the most comprehensive market database such as TRACE, a custodian's database contains information about both transaction prices and the holdings and turnover of various investors, which will be used in combination in constructing our liquidity measure.

#### 2.2 A Comparative Analysis of the US Corporate Bond Database

The SSC holdings database represents a comparatively large sample of the whole market for US corporate bonds, in terms of both holdings as well as transactions. It also covers a relatively long history from January 1994 to June  $2006<sup>5</sup>$  We first present some evidence of the representative nature of the database in relation to the universe of US corporate bonds.

Table 1A presents the composition of our bond database broken down by industry, as compared to the total universe of US corporate bonds. The universe is defined based on data from Reuters, for the amount of bonds outstanding, in various industry segments as of June 30, 2006. As can be seen from the table, which presents the amounts outstanding in the various industry categories, our total sample represents about  $14.52\%$  of the whole market.<sup>6</sup> We can see from this table that our database provides a good representation of the cross-section of bonds outstanding. The only significant deviation occurs with banks and the telephone industry. Banks are over-represented in our database (19.87% vs 13.96% of the total universe). In contrast, our database is underweight in telephone (4.98% vs 8.27% of the total universe).

Table 1B presents a similar disaggregation of our data in relation to the universe of US corporate bonds, based on Moody's credit rating. Our database's credit quality composition exhibits a

 $5$ Unfortunately, some of the bond characteristics were not available in our database for the entire sample period. Consequently, we have restricted our empirical analysis to the period from January 2000 to June 2005.

 ${}^{6}$ We use the industry categories defined by Reuters.

somewhat greater deviation from the universe, as compared to the industry composition in Table 1A. However, our database still remains reasonably representative of the universe, with our data being over-represented in the high quality (Aaa and Aa) segment (12.20% and 25.72%, in the SSC sample, respectively, compared with 7.49% and 18.61% in the universe) and under-represented in the low quality (C and ungraded) segment  $(0.21\%$  and  $7.32\%$ , respectively, compared with  $0.66\%$ and 9.53% in the universe). This is not surprising, considering that our holdings database consists of portfolios of institutional investors.

Table 1C presents the disaggregated statistics for our database in relation to the universe, based on maturity. Again, our database remains reasonably representative of the universe, although it is somewhat under-represented for the long maturity segment (greater than 10 years) - around 17.89% of the SSC sample, compared to 24.69% in the universe - and over-represented for very short maturities (less than 1 year) - 22.23% in the SSC sample, as opposed to 12.32% in the whole market.

We turn next to the transaction statistics for our database versus the whole market, based on data from the Bond Market Association (BMA).<sup>7</sup> This is presented in Table 2. We cannot draw conclusions about the representativeness of the trades in our database for the various cross-sections, due to the lack of comparable benchmarks for corporate bond transactions in the total universe. However, we do see that the database comprises of over 6% of the average daily trading volume in US corporate bonds.<sup>8</sup> Furthermore, this level does not fluctuate very much through time. The stability of trading volume gives some indication that the cross-sectional patterns, presented in Tables 1A, 1B and 1C, are fairly stable.

Based on the above comparisons, we can conclude that our database is reasonably representative of the whole market for US corporate bonds. This conclusion holds in terms of the broad characteristics of the bond market, both for the cross-sectional holdings of the bonds and the way this cross-section moves through time. We conjecture, therefore, that the conclusions we draw from

<sup>7</sup>This database does not provide transactions statistics disaggregated into the various categories mentioned earlier. Further, the statistics are available only on a monthly basis, and that too, only since January 2003.

<sup>&</sup>lt;sup>8</sup>We believe that this figure may be on the conservative side, since we generally notice only one side of a trade, in our database, as opposed to both sides in the market, at large, had such data been available. Also we restrict ourselves to the sample set of bonds, for which clean security level information and rating data is available, which is a subset of our data.

this database should have relevance for the market as a whole.

#### 2.3 Characteristics of the US Corporate Bond Database

Our goal in this paper is to conduct a broad analysis of the illiquidity in the US corporate bond market, based on the transactions in our database. Table 3 provides data on the illiquidity of the corporate bond market based on the frequency of trading to support our claim that this market is highly illiquid. We see from this table that, across the years, there are very few bonds that trade every day in our sample. The number of bonds that trade approximately every day (defined as over 200 days in the year) varies between 0 and 6; this is out of a sample of roughly 19,000 bonds. Even considering a level of trading of at least once a year as relatively liquid, the percentage of the total number of bonds in our sample that would be defined as liquid is between 22% and 34%, each year. A large proportion of the bonds - over  $40\%$  - do not even trade once a year. These statistics throw some light on the problem of illiquidity in the corporate bond market and suggest that it would be futile to look for liquidity measures based only on market micro-structure data.

We now go into greater detail regarding the characteristics of the corporate bonds that are traded, based on our data set, over the period 2000-2005. We give an indication in Table 4 about the trading characteristics of corporate bonds that trade in the marketplace. In general, we see that bond issues are split into one of eleven broad industry categories that we define (these are in line with the categories used by Reuters). The percentages in the various industry categories were fairly stable over the course of the 2000-2005 period. Bonds in the financial services industry (the banks and the other financial categories) traded the most during the sample period. This is not surprising as financial services industry is the biggest issuer of corporate debt - in 2006, more than one-third of all new debt issues came from firms within this industry. Most financial services firms such as banks and insurance companies are highly leveraged entities, with substantial debt obligations on the right-hand sides of their balance sheets.

Table 5 shows how the trading characteristics of bonds by credit has been changing through time. During the early part of the sample period (2000-2005), a higher percentage of investment grade bonds was traded. For example, in 2000, 76% of bond issues traded were rated as investment grade(with the rest being in the speculative category). As we progress through time, however, this proportion decreased to 66% in 2005. Significant changes occurred in the marketplace, during the sample period. Equity markets dropped substantially during the early 2000s, indicating that the probability of default of most firms increased, as well. This conclusion is supported by the fact that credit spreads also increased significantly during this time period. Therefore, if rating agencies were doing a reasonably good job, the conclusion that more bonds in the marketplace were getting rated below investment grade, is natural.

We next present the trade data analyzed in terms of various bond characteristics such as maturity, time since issuance, face value and frequency of trading. We do this for each year, for data below each cumulative decile, during our sample period, 2000-2005. Table 6 displays the maturity structure of corporate debt traded in the marketplace. The average maturity of debt has not fluctuated much during the sample period. Table 7 shows that the time since issuance of traded debt has been fairly steady from 2000 until 2005.

Table 8 shows the distribution of the outstanding face amount of all debt traded in the market. The table shows that the median face value amount of trades has increased substantially over the last five years. For the median bond, the face amount outstanding increased from \$ 175 million in 2000 to \$ 250 million in 2005. For the top decile, the corresponding numbers were \$ 500 million in 2000 going up to \$ 800 million in 2005; for the bottom decile, the face amount outstanding went up from \$ 25 million in 2000 to \$ 100 million in 2005.

Table 9 gives us a sense of the amount of trading activity that occurs in the US corporate bond markets. Table 9, which is a variation of Table 3, shows the average number of days that pass between trades for a bond issue, for those bonds that are actually traded. As shown in Table 3, most bonds did not have any trades for many years. We exclude them from the analysis presented in Table 9. For the median traded bond, the average time between trades varied between 12 days and 18 days within the sample period.<sup>9</sup> For the median stock, in comparison, this value is more of the order of minutes. For the most liquid stocks, this statistic could even be of the order of seconds. Therefore, we see from Tables 8 and 9 that the corporate bond market is orders of magnitude more

<sup>&</sup>lt;sup>9</sup>There are roughly twenty two trading days in a calendar month.

illiquid than the stock market, even if we were to consider the liquid segment of corporate bond market (as represented by the traded set).

#### 2.4 Liquidity Measurement

The previous section provided strong evidence in support of the conclusion that the U.S. corporate bond market is extremely illiquid. Therefore, in many ways, this market seems a much more relevant setting to study the problems of illiquidity and its consequences, compared to equity markets, since illiquidity is a significant issue in the corporate debt market. However, one important problem remains. Most corporate bonds rarely trade. This makes it difficult to distinguish between whether a given bond is more liquid than another, particularly if both bonds do not trade for several days or even months. For example, if one bond trades six times a year and a second one trades three times a year, the amount of trading in both cases is too small to conclude that the first bond is twice as liquid as the second. Our proposed measure gives a better sense of the relative liquidity of the two bonds.

In a dealer, or OTC, market what really determines the liquidity of a security is the ease with which a dealer can access a security. For example, if a buy order comes in to a dealer, she could supply that order out of her own inventory, or she could try to source the bonds from the inventory of one of her other customers. In other words, the dealer could "work the order" by contacting customers to see if she can convince someone to sell her the bonds to fill the buy order.<sup>10</sup> Consider the case when she is trying to call customers to fill the buy order. If the bond issue of interest is held primarily by funds with high turnover (hedge funds, for example), it should be easier for the dealer to contact one of them and to convince them to sell her the needed bonds, than if the bonds were held primarily by funds with low turnover (insurance companies, for example).<sup>11</sup> This is because the high turnover funds are used to trading in and out of securities with high frequency, at least, relative to many fixed income investors, who tend to be "buy and hold till maturity"type of investors. Thus, they could be more easily convinced to trade a particular security they are

 $10$ The dealer will, of course, try to buy the bonds at a lower price from the customer than the price at which she will fill the buy order. Thus, she earns a fee for her "search services."

 $11$ Of course, one can define a whole continuum of customers, in terms of their propensity to trade, rather than the two referred to in the example.

holding. Therefore, whether a bond issue experiences a great deal of trading volume or not, we can say that a bond issue is more liquid in our sense, if it is more accessible by dealers. We define such access in terms of the turnover of the investors holding the bond issue. In the context of the accessibility of a security, the search costs and times are likely to be lower for bonds that are held primarily by high turnover agents.

This measure of accessibility of a security is not a direct measure of liquidity, but rather a more *latent* measure. In order to measure latent liquidity, we need to be able to determine, for each bond issue, which of the many types of investors actually holds the issue and the aggregated weighted average turnover of all the investors holding the issue. If the weighted average turnover of all the funds holding a particular bond issue is high, then we say that the bond issue has high latent liquidity. In other words, it is more accessible, relative to another bond that has lower latent liquidity. Latent liquidity, in that sense, can be thought of as the degree to which it is held by investors who are expected to trade more frequently, based on historical trading patterns.

Once again, a custodian is in an ideal position to obtain the information needed to calculate latent liquidity. Custodians are aware not only about the transactions level information, but also the individual portfolio holdings. Therefore, if we look at the historical custodial holdings database, we can calculate a twelve-month historical turnover number for all portfolios. For any particular bond issue, we aggregate across all the investors holding that issue, to calculate a weighted average turnover measure. This statistic becomes our latent liquidity measure for that particular bond.

More formally, we define the fractional holding of bond  $i$  (as a percentage of the total outstanding amount of the bond issue in our database) by fund j at the end of month t as  $\pi_{j,t}^i$ . Also, we define the average portfolio turnover of fund j from month t to month  $t - 12$  as  $T_{j,t}$ , where the portfolio turnover is defined as the ratio of the value of fund j at the end of month t to the dollar trading volume of fund j from month t to month  $t-12$ . Latent liquidity for bond i in month t is defined as

$$
L_t^i = \sum_j \pi_{j,t}^i T_{j,t}
$$

Therefore, we define latent liquidity for any bond  $i$ , at any time  $t$ , as the aggregate weighted-average level of turnover of the individual funds holding bond i.

The most convenient feature of this measure is that it is based entirely on aggregate investors' holdings and does not require individual transaction details. In fact, as we have already said, the lack of sufficient corporate bond transaction data is at the heart of illiquidity in bond markets. Therefore, this measure can be calculated even in the absence of trading in a particular bond, and hence, especially convenient in the case of illiquid markets. Furthermore, this measure can be calculated quite accurately, on a monthly basis, for every public bond issue, given the unique nature of our database, which consists of data on both transactions, as well as holdings of a large set of investors in the market. It should be noted that even if a larger set of trading data eventually became available from the TRACE database, the metric we propose would require, in addition, information regarding the holdings and turnover of individual investors in the market, which is usually proprietary.

Figures 1 through 5 present the patterns of changes in latent liquidity with respect to changes in certain bond characteristics, to show how they accord with more casually stated stylized facts. To generate these figures, after calculating a latent liquidity number for each US corporate bond in our database, we ranked bonds into percentiles (scaled 0-1, in our empirical work and presented in the graphs and tables), based on their latent liquidity, where 0 represents the lowest liquidity level and 1 the highest liquidity level. For each bond characteristic, the latent liquidity percentile rank is averaged across bonds with a particular value of the characteristic. The graphs represent the relationship between the (average) latent liquidity and the particular bond characteristic.

Figure 1 plots the (average) latent liquidity of bonds in relation to their age, from the time they were first issued, until maturity. We observe that bonds are at their peak latent liquidity levels when they are just issued. Their latent liquidity level decreases steadily after issuance, until final maturity. This is consistent with, but more specific than, the casual evidence that "on-therun" bonds are more liquid than their "off-the-run" counterparts. The conjecture that emerges is that many bonds are initially placed into high turnover funds, who then "flip" the bonds to lower turnover (usually, buy-and-hold) funds. We see that latent liquidity values are greater than 0.5, on average, for bonds with an age of less than one year, and, in general, decrease over time to a value of less than 0.3, for bonds with an age greater than 26 years.

Figure 2 shows the relationship between (average) latent liquidity and issue size. Generally speaking, there is a positive correlation between issue size and liquidity. The biggest improvement in liquidity occurs for issue sizes below \$ 600 million. The liquidity is relatively flat again, until a size of \$3 billion is reached, when it increases once again. This could possibly have to do with the inclusion of bonds of size greater than \$3 billion into indices such as the Lehman Aggregate Index. Figure 3 provides a plot of the (average) latent liquidity versus time to maturity for bond issues. We observe that the longer the maturity of a bond, the higher its latent liquidity, although there are clear jumps in the pattern, at certain maturity levels. The jumps in this figure are initially surprising, but easily explained - they are due to bond issues of "standard" maturities. For instance, bonds with a 10-year maturity are of two types: bonds that were issued in the past and are now down to 10 years to maturity i.e., "off-the-run" bonds and bonds that have just been issued i.e., "on-the-run" bonds. However, bonds with a 11-year maturity are likely to be mostly "off-the-run" bonds (because 11 years is seldom chosen as a maturity time for newly-issued bonds). Therefore, the significantly higher latent liquidity of the "on-the-run" bonds at the 10-year maturity level results in a substantially higher latent liquidity measure at the 10-year level vs. the 11-year level; hence, the observed jump in the graph. The same result holds at typical maturity points for new issues, such as at 20, and 30 years.

Figure 4 presents the (average) latent liquidity as a function of coupon rates over the sample period. There is no clear pattern in this relationship, because coupon effects are confounded by credit rating, age, maturity and issue date, since there are strong correlations between the coupon rate and these bond characteristics. In a loose sense, it appears that issues with a higher coupon rate enjoy greater liquidity than those with a lower coupon. However, it appears that zero coupon bonds are more liquid than bonds with a promised coupon rate of up to approximately 10 %. This may be due to the desirability of zero coupon issues for implementing hedging and cash matching strategies.

Figure 5 represents the (average) latent liquidity as a function of Moody's credit rating. We observe that latent liquidity steadily improves as we move down in credit quality. However, since the relationship is inherently multi-factor in nature, with independent variables that are, to some extent, correlated with each other, we need to examine it further through regression analysis. We turn to this empirical analysis in the next section.

# 3 The drivers of bond liquidity

In this section, we try to discern which features of a bond lead to better liquidity. To investigate this question, we conduct a series of regressions where the dependent variable is a particular metric of liquidity for a bond in the database at a point in time, while the independent variables are a set of the bond's characteristics. In order to perform these regressions, we compute the latent liquidity of each bond as of the beginning of a quarter. Since latent liquidity does not require transactions in the bond, we are able to conduct regressions where latent liquidity is the dependent variable on all the bonds in our database. In order to better understand differences between traded and non-traded bonds, we also run these regressions separately on bonds that have traded at least once in a quarter, and on bonds that have not traded at all. From our earlier tables, this means that we restrict ourselves to slightly less than half the database.

In the analysis below, we use two trade-based liquidity measures for a bond. The first is trade count: the number of trades that occur in a particular quarter. The second is trade volume: the average market value of trades for the bond each quarter.<sup>12</sup> The purpose of using the more conventional measures of liquidity is to compare the empirical results we obtain for latent liquidity with those for more conventional measures. For trading volume and the trade count, we are, for obvious reasons, restricted to using only bonds that have traded at least once a quarter.

We observe that there are large outliers in the measures. Hence, for all the liquidity measures we consider (including latent liquidity), we convert the liquidity measures into a percentile rank within each quarter. Each bond is ranked on a scale of 0 to 1 (from less liquid to more liquid) within a quarter. Thus, we interpret these measures to be cardinal rather than ordinal measures of liquidity. This cardinal measure has the additional advantage of making the measures comparable from one quarter to another regardless of changes in overall trading volumes in the market, or

 $12$ We have also run these regressions using the number of days on which a bond trades as a measure of liquidity. However, there is a very high correlation between trade count and the number of days traded, and the results are very similar to those we observe for the trade count, and are not reported here.

changes in coverage.

We first examine the correlations between our measure of latent liquidity and the two tradebased measures of liquidity, the results of which are presented in Table 10. Only bonds that traded at least once in a given quarter are included in this sample. The correlations between the two trade-based measures are fairly high, as is to be expected, since they all measure the frequency and size of trades. However, the correlations between latent liquidity and the trade-based measures are more modest. Given the relatively infrequent trading in even the most liquid US corporate bonds, apparently the trade-based measures do not quite measure the same latent liquidity effects that are captured in our measure. We next investigate the relationship between the three measures and various characteristics of the bonds, in separate regressions, the results of which are presented in Tables 11.

Table 11 presents results from the regressions of these liquidity measures, on independent variables related to the characteristics of the bonds. These regressions were performed on quarterly data from January 2000 to July 2006. In these regression, we use latent liquidity, trade count and trading volume (in percentile ranks from 0 to 1) as the dependent variables, for both the traded and non-traded sets of bonds. All columns present the coefficients and z-statistics of a random effects regression, where the observations are clustered by quarters to account for correlations between the residuals in every quarter.<sup>13</sup>

As one might expect, liquidity seems to be strongly correlated with the face amount of a bond outstanding, or the issue size of a bond. The larger the issue size, the more liquid is the bond. A preview of this result was illustrated in Figure 2, where we saw that when the size of the issue falls below \$1 billion, the smaller an issue size, the less liquid is the issuance. However, Figure 2 also showed that for amounts above \$1 billion, issue size seems to have only a small effect on liquidity. For smaller issue sizes, liquidity clearly diminishes with size. Smaller-sized issues do not appeal to a broad class of investors, since it would be difficult and costly to acquire a large position, which some institutional investors may require. The link between issue size and liquidity has also been identified as important by other researchers such as Hong and Warga (2000), Alexander, Edwards,

 $13$ It is possible that residuals are correlated for each bond across quarters. In order to account for this, we also perform Fama-Macbeth regressions using the cross-section of bonds in every quarter, as discussed below.

and Ferri (2000), and Hotchkiss, Warga, and Jostava (2002).

The current age of the bond since issuance has a strong negative correlation with liquidity, i.e., a bond with a greater age (one that has been outstanding for a longer time) has less liquidity. This is the well known "on-the-run" vs. "off-the-run" effect (see for instance Sarig and Warga (1989), Warga (1992), Chakravarty and Sarkar (1999), Hong and Warga (2000), Schultz (2001), and Hotchkiss, Warga, and Jostava (2002)). When a bond is initially issued, it is "on-the-run" and has much higher liquidity than some time later, after it has been outstanding for a while and becomes "off-the-run".

The credit quality of a bond appears to be inversely correlated to liquidity, i.e. the higher the probability of default (and therefore the lower the credit rating) the higher the degree of liquidity. This is a surprising result, because most people tend to associate high credit quality with high liquidity. The simple explanation here is that bonds that have a high credit quality are usually held by long-term "buy-and-hold" investors such as insurance companies, which have long-term liabilities and hold fixed income assets for asset-liability matching reasons, because these bonds are less likely to default and force a portfolio re-balancing. In addition, low-grade issues have a greater probability of rating migration, necessitating more frequent re-balancing.

The current maturity of the bond seems to have a negligible effect on the liquidity of the bonds for all the measures. However, some effects are observed using the original maturity of the bonds at the time of issue. The "original maturity" variables are all dummy variables indicating the maturity of the bond when it was issued. From the coefficients here, it appears that bonds with lower original maturity, such as 5 and 7 years, have greater latent liquidity than those with an original maturity of 10 years or 30 years. Again, one explanation here is that long term "buy-andhold" investors such as insurance companies (which hold a substantial amount of the total bonds outstanding) have long-dated liabilities, against which they match long-dated assets. Once they "find" these assets, they tend to hold them. However, when we use the trading volume and trade count as measures of liquidity, these effects are not as pronounced. It appears that bonds with non-standard original maturities (other than 5, 7, 10 or 30) are the least traded. We also see that if a bond's issuer is classified as being an industrial company, the bond tends to be less liquid, i.e., it tends to be held by low turnover funds. On the other hand, if a bond is from a financial issuer, it appears to be held by more active funds, although this does not translate into a greater amount of trading in the bonds. Utilities, however tend to have less liquidity as reflected in all three measures. Privately-placed bonds tend to have lower liquidity in our sample using the trade-based measures, however, when traded, they seem to be held by the more active funds, although the significance of the coefficients is in doubt. This issue needs to be examined more closely in future research.

Issuers generally have the choice of including various provisions into bond indentures. These provisions include option features that render the bond callable or putable, or making the bond convertible into equity. In our results, callable bonds tend to have higher trading volume and trade count. The difference in the coefficients in the latent liquidity regressions between traded and nontraded callable bonds is intriguing, and shows that while callable bonds that are liquid are generally held to a greater extent by higher turnover funds, callable bonds that are not liquid are held, to a greater extent, by lower turnover funds. The "puttability" of a bond makes it more attractive to higher turnover funds, although they are not highly traded. These results are surprising: one might think that adding complexity such as optionality to a bond would make it more difficult to trade, since the complexity may prevent less sophisticated investors from investing in these bonds, thus limiting the pool of potential investors. The results are also conflicting with respect to the convertibility feature of bonds. The trade-based measures show a negative relationship between liquidity and the presence of this feature. In contrast, the latent liquidity regression results show a positive relationship between convertibility of a bond and its liquidity. Other characteristics of a bond such as whether the bond pays a fixed or floating coupon payment, or the periodicity of the coupon payments, do not seem to affect the liquidity of a bond in a systematic manner. The zero-coupon nature of some bonds seems to make them more attractive to active funds; however, these are not very highly traded, making it likely that they are primarily held for hedging purposes.

Some general comments about the various findings in this section are in order. First, we note that the coefficients on the drivers of latent liquidity between traded and non-traded bonds are consistent both in magnitude and in direction. The only major differences seem to be on how callability, variable interest rates and private placement affect latent liquidity for traded and nontraded bonds. These effects themselves are interesting and warrant further investigation. These results give us a strong indication that the latent liquidity measure can be extended to the illiquid segment of the US corporate bond market. The fact that latent liquidity is a consistent measure, and does not have a sample bias, leads us to believe that it can be used as a measure of liquidity uniformly across all bonds in the US corporate bond universe. It can be applied not only to the relatively liquid bonds where trade data are available but also to the illiquid segment of the US corporate bond universe, for which trade-based measures of liquidity cannot be obtained. Second, as expected, the drivers of latent liquidity, trading volume and trade count - amount outstanding, age, rating class and industry sector - seem to be the primary drivers of liquidity. Third, there are some important differences between the effect of certain bond characteristics, which are secondary drivers. Fourth, we also find that the power of these regressions is higher for latent liquidity because of the larger number of observations available for this metric, since it can be computed even when no transaction occurs in the subsequent period.

In order to check that our results are robust for possible within-bond and across quarter autocorrelation in residuals, we perform quarterly cross-sectional regressions, and then aggregate the coefficients across quarters, according to the Fama-Macbeth method. The results of these are presented in Table 12. The coefficients are very similar to those we obtain under our random effects specification, indicating that our results are robust to either specification. Table 13 presents a summary of the sign and the significance of each of these coefficients when performed on the cross-section of bonds available for each quarter.

# 4 Latent Liquidity and transaction costs

We demonstrate an application of the concept of latent liquidity in the prediction of transaction costs in the bond market, and in doing so, present a validation of our measure. The recent literature on transaction costs contains many models for estimating transactions costs. Bessembinder, Maxwell and Venkataraman (2005) use data reported by insurance companies to the National Association of Insurance Companies in order to estimate round-trip transactions costs for a limited set of bonds using a signed-variable approach. Using the same data-set, Goldstein, Hotchkiss and Sirri (2005) establish that transaction costs have decreased after the introduction of reporting on TRACE. However, both these methodologies require the use of signed trades, and are limited in scope to the trades reported by insurance companies.

Unfortunately, TRACE data as made available by the NASD, does not have buy/sell identifiers for trades, although it covers a much broader segment of the market, both in terms of the cross section of instruments traded, and number of market participants. Hence, for the purpose of estimating transaction costs in bonds, we use the limited dependent variable approach of Chen, Lesmond and Wei (2005). This method allows us to form estimates of transaction costs only on the basis of the last traded prices for every day in the TRACE database. A detailed explanation of the method is given in appendix A. The estimated transaction costs are in percentages normalized by the price of the bond. Our estimates of transaction costs are comparable in magnitude to those obtained by Chen, Lesmond and Wei (2005), both across rating and maturity classes. The only point of departure from their method is in our use of transactions reported on TRACE for the computation of return series in bonds, as opposed to their approach of using Datastream daily prices, which represents quotes from a much smaller set of contributors.<sup>14</sup>

Univariate regressions of the transaction cost estimates on latent liquidity for each quarter are presented in Table 14. The coefficient on latent liquidity is consistently negative for all quarters. In an overall sense, going from a percentile rank of 0 to 100% (0-1 in our scale) leads to a reduction in estimated transaction costs of around 200 basis points. However, if latent liquidity is indeed a better measure of liquidity than realized measures such as trade count or trade volume, we would expect latent liquidity at the beginning of a quarter to have explanatory power over and above the realized trading count during the quarter, and bond-specific variables that primarily drive liquidity such as outstanding amount, coupon, rating and age. We test this relationship on quarterly estimates of transaction costs in our bonds for the period from July, 2002 (when substantial reporting on TRACE begins) to June, 2006. These results are reported in Table 15. The estimation of transaction costs

<sup>&</sup>lt;sup>14</sup>We also attempted an alternate specification using changes in interest rates and the changes in the credit default swap (CDS) premium, obtained from a leading broker in the CDS market, for the issuer of a bond as a measure of its "true" return. However, the CDS market itself is liquid for only a fraction of all the bonds traded in the market and often has fewer observed returns than the bond itself. Thus, such an analysis severely restricts the number of bonds for which we can estimate transaction costs. It is possible to pursue this issue further as the liquidity of the CDS market improves.

requires us to have bonds with a minimum of five trade observations in any given quarter. This requirement, along with the fact that we are considering an intersection of trades reported on TRACE with the SSC database restricts the number of bonds in our sample for every quarter to the numbers that are reported in Table 15. It is clear that with the passage of time, trading activity as reported on the TRACE database has increased, as evidenced by the increasing number of bonds available in our sample.

Even after controlling for other variables, the coefficient on the latent liquidity percentile is consistently negative for all the quarters in our sample period, and is significant for nine out of the sixteen quarters in our data-set. On an average, after controlling for realized liquidity in the form of trade count and bond characteristics that primarily drive liquidity in bonds, we still find that there is a 105 basis point difference in transaction costs between the most liquid and the least liquid bonds in our sample. We also find that amount outstanding has significant explanatory power for transaction costs. An increase of an order of magnitude in the issue size leads to a reduction of about 91 basis points in the transaction costs. The coefficient on the amount outstanding is also strongly negative, and so is the coefficient on the trade count variable. However, once we control for latent liquidity, age and transaction volume appear to lose most of their explanatory power. Thus, the explanatory power of latent liquidity is clearly over and above both measures of realized liquidity, as well as bond-specific variables.

This result is important because it shows that it is not only bond characteristics and the realized liquidity of a bond that drives its transaction costs, but also its accessibility, as measured by latent liquidity. It is also significant in these regressions that latent liquidity has a true predictive relationship, since we use beginning of the quarter latent liquidity to predict transaction costs within the quarter, over and above the trade count during the quarter. Furthermore, the consistency of the coefficients across quarters gives us confidence that our results are robust across time. These results give us confidence that latent liquidity is indeed a meaningful and viable measure of liquidity that can be applied to both traded and non-traded bonds.

### 5 Latent liquidity and price impact

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Another way through which illiquidity manifests itself is in the price impact of trading a security. Several microstructure-based measures of price impact have been documented in the literature, of which the measure proposed by Amihud (2002), based on the  $\lambda$  measure of Kyle (1985), is the most intuitive and simple to implement. We use the Amihud measure of price impact, which is simply the average ratio of the absolute return in a bond to its trading volume in any given period. If the absolute return during a day t is  $|r_t|$  and the trading volume on that day is  $V_t$ , the average Amihud measure over a period of T days is given by

$$
ILLIQ_T = \frac{1}{T} \sum_{t=1}^T \frac{|r_t|}{V_t}
$$

A higher value of the measure implies a greater price impact of trading, and consequently, lower liquidity. Price impact is also positively correlated with transaction costs.<sup>15</sup> It is useful to assess the predictive power of the other liquidity variables in assessing price impact as a check on the results of the previous section. However, this measure of liquidity in the bond markets presents a few implementation challenges; we need to make some decisions on how we treat the data, which need to be made explicit. We use transactions reported on TRACE in order to compute the ILLIQ measure for every bond for every quarter, provided we observe at least five market lot trades (defined as a minimum of USD 1 million of face value of the bond traded) in the bond in that quarter. The return on the bond is computed using the last traded "clean" prices of market lots on a given day only, and thus ignores the accrued coupon. This screen avoids using price observations from small trades that may not be reflective of the true return. In addition transactions greater than 5 million on TRACE are reported as 5MM+, and transactions greater than 1 million are occasionally reported as 1MM+. We assume these to be 5 million and 1 million respectively. The ratio of daily absolute returns to the daily trading volume is averaged over a quarter for every bond. Days on which there are no trades represent a zero return and a zero trading volume, and are thus

<sup>&</sup>lt;sup>15</sup>The reader is encouraged to refer to Amihud (2002) for a detailed discussion of the measure.

not included in the averaging. For the set of bonds for which we have computed transaction cost, this gives us a quarterly measure of price impact of trading. Because there tend to be large positive outliers in the measure, we use the log of the measure in our regressions.

Univariate regressions of the log of the Amihud price impact measure on latent liquidity for each quarter are presented in Table 14. The coefficient on latent liquidity is consistently negative for all quarters. In the overall sense, going from a percentile rank of 0 to 100% leads to an eight-fold reduction in the price impact.

We perform quarterly regressions of the Amihud measure on bond characteristics such as coupon, rating, issue size and age, and on the average trade count during the quarter, and on the latent liquidity of the bond during the quarter. Table 17 presents these results. We find that the latent liquidity measure has explanatory power, over and above the other measures, including the realized trade volume measure. The coefficients have similar signs to those that we observe in the case of transaction costs. A larger issue size is associated with lower price impact. Age is positively and significantly associated with price impact. Crucially, longer dated bonds tend to have a higher price impact of trading than shorter dated bonds. The realized trade volume is negatively and significantly associated with the trading volume. However, we find that latent liquidity has additional explanatory power, over and above the transaction-based measures. On an average going from the lowest latent liquidity to the highest latent liquidity bond (percentile rank 0 to 1), we find that other things remaining the same, the ILLIQ measure is almost halved.

# 6 Conclusion

In conclusion, this paper presents a new measure of liquidity called latent liquidity, and then applies this measure to a unique corporate bond database to analyze the characteristics of bonds that lead to higher liquidity. Unlike conventional measures of liquidity, such as trading volume and bid-ask spreads, latent liquidity does not use transaction information. Instead, it uses information about the ownership of securities to discern the accessibility of a security by a securities dealer. Therefore, latent liquidity has the important advantage of being able to provide a measure of liquidity in situations of low trading intensity, when transaction data are insufficient to compute traditional microstructure-based measures of liquidity, but where liquidity is still an important issue.

We apply the latent liquidity measure to the relatively illiquid corporate bond market in order to determine the characteristics of corporate bonds that lead to higher or lower liquidity. We find that credit quality, the age of a bond, the size of a bond issue and the industry sector are the primary drivers of liquidity. In addition, the original maturity value of a bond at issuance date, and provisions such as a call, put, or convertible options all have an impact on liquidity. If illiquidity is priced (i.e., investors charge a liquidity risk premium), then the results of this paper indicate that the design of a bond can have a strong influence on the cost of the bond to the issuer, and the choice of which bond to hold (from the same issuer) can have a strong influence on the returns of an investor.

The directional relationship between liquidity and the bond characteristics is compared across the various liquidity measures. For the most part, the results for latent liquidity agree with the three traditional measures based on transaction data. However, in certain cases such as original maturity of the bond, the face value outstanding and the optionality features of the bonds, latent liquidity seems to agree with intuitive reasoning, whereas the other measures do not always behave consistently. We also determine that latent liquidity does not have a sample bias and can be used as a measure of liquidity uniformly across all the bonds in corporate bond universe. It can be applied not only to the relatively liquid bonds where trade data is available but also to the illiquid segment of the corporate bond universe, where transactional data is rare or unavailable and where traditional measures (based on transactional data) cannot be applied with any statistical confidence.

Latent liquidity has the potential to predict transaction costs of trading in the illiquid corporate bond market. We demonstrate this by using data on all trades in bonds on a smaller subset in our sample, we also determine that latent liquidity has greater explanatory power that either transaction volume or bond specific characteristics on transaction costs in bonds, showing that it is not only the realized liquidity of the bond that matters for trading costs, but also the turnover of agents holding a bond, as measured by latent liquidity. Another manifestation of liquidity is in the form of the price impact of trading. We use the Amihud ILLIQ measure to compute the average quarterly price impact in bonds that trade actively on TRACE. We find that latent liquidity has explanatory power for price impact, both unconditionally, and over and above other bond specific variables. Hence, latent liquidity has the potential to predict both transaction costs and price impact in the illiquid corporate bond market.

We believe that this research can also pave the way to explain some portion of the yield spreads on corporate bonds that cannot be explained by structural models of corporate credit risk. In future research, we will investigate this directly by incorporating our liquidity factors in structural models of credit risk. It would also be interesting to examine the significance of liquidity in determining asset returns. In particular, we propose to use this measure in explaining the crosssectional variation in bond yield spreads, over their Treasury and swap rate benchmarks, after accounting for default risk. Based on the evidence presented in this paper, it is likely that latent liquidity will explain at least part of the cross-sectional variation in bond yields, apart from the default premium. Our research will also address the issue of liquidity risk of corporate bonds, and whether or not, it is systematic in relation to the market-wide liquidity. An additional question that we will attempt to examine is whether liquidity risk is, in fact, priced, and whether it is an important element of the total yield spread of corporate bonds over comparable Treasury bonds.

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# Appendix A

Chen, Lesmond and Wei (2005) use daily observations of bond returns to generate bond-level liquidity costs. They assume that the return generating process for bonds is driven by two factors: an interest rate factor and an equity market factor. We provide a brief exposition of their methodology.<sup>16</sup>

The true return generating process for any bond is then given by:

$$
R_{j,t}^* = \beta_{j,1} \text{Duration}_{j,t} \Delta R_{f,t} + \text{Duration}_{j,t} \beta_{j,2} R_t^{\text{S\&P}} + \epsilon j, t \tag{A-1}
$$

where  $R_{j,t}^*$  is the true unobserved return on the bond,  $\Delta R_{f,t}$  is the change in the five-year risk-free interest rate and  $R_t^{S\&P}$  is the daily return on the S&P index. Accounting for transaction costs, the realized return on the bond is given by

$$
R_{j,t} = R_{j,t}^* - \alpha_{1,j} \qquad \qquad \text{if } R_{j,t}^* < \alpha_{1,j} \text{ and } \alpha_{1,j} < 0
$$
\n
$$
R_{j,t} = 0 \qquad \qquad \text{if } \alpha_{1,j} < R_{j,t}^* < \alpha_{2,j}
$$
\n
$$
R_{j,t} = R_{j,t}^* - \alpha_{2,j} \qquad \qquad \text{if } R_{j,t}^* > \alpha_{2,j} \text{ and } \alpha_{2,j} > 0 \qquad (A-2)
$$

where  $R_{j,t}$  is the observed return,  $\alpha_{2,j}$  is the effective buy-side cost and  $\alpha_{1,j}$  is the effective sell-side cost. Assuming that daily bond returns are normally distributed gives a log likelihood function for

<sup>&</sup>lt;sup>16</sup>For a complete treatment of estimating transaction costs using limited dependent variable models, refer to Lesmond, Ogden and Trzcinka (1999) and Chen, Lesmond and Wei (2005).

the system, that can then be estimated.

$$
LNL = \sum_{1} Log \left( \frac{1}{(2\pi\sigma_j^2)^{1/2}} \right)
$$
  
\n
$$
- \sum_{1} \frac{1}{2\sigma_j^2} \left( R_j + \alpha_{1,j} - \beta_{j,1} Duration_{j,t} \Delta R_{f,t} - Duration_{j,t} \beta_{j,2} R_t^{S\&P} \right)^2
$$
  
\n
$$
+ \sum_{2} Log \left( \frac{1}{(2\pi\sigma_j^2)^{1/2}} \right)
$$
  
\n
$$
- \sum_{2} \frac{1}{2\sigma_j^2} \left( R_j + \alpha_{2,j} - \beta_{j,1} Duration_{j,t} \Delta R_{f,t} - Duration_{j,t} \beta_{j,2} R_t^{S\&P} \right)^2
$$
  
\n
$$
+ \sum_{0} Log \left[ \Phi_{2,j} - \Phi_{1,j} \right]
$$
 (A-3)

where  $\sum_{1}$  represents the negative non-zero observed returns,  $\sum_{2}$  represents the positive non-zero observed returns, and  $\sum_0$  represents zero observed returns.

The round trip transaction costs (expressed as a percentage of bond price is then obtained as  $\alpha_{2,j} - \alpha_{1,j}$ . For the purpose of estimating transaction costs in our dataset, we include all bonds for which we have observations in the TRACE database and for which latent liquidity and other bond characteristics are available from the SSC database. We match bonds on the basis of their Committee on Uniform Securities Identification Procedures (CUSIP) number. Returns are observed whenever a trade takes place in the bond, and are zero otherwise. We reject bonds that have less than five trades (five measured) returns during a quarter in the TRACE database. We take the last traded price of a bond on a day as a measure of its end of the day price. We use the constant maturity five year treasury yield to compute changes in the interest rate factor in equation A-1 and contemporaneous return on the S&P index as a measure of the equity market return.<sup>17</sup> Quarterly measures of transaction costs so estimated are used in the regressions in Table 15.

 $17$ We also attempt an alternate specification using the interest rate and the changes in the credit default swap premium (obtained from a leading broker in the CDS market) for the issuer of a bond directly as a measure of the changes in its "true" return. However, the CDS market is liquid for only a fraction of all the bonds traded in the market and often has fewer observed returns than the bond itself. Thus doing so severely restricts the number of bonds for which we can estimate transaction costs. Moreover, the magnitude of the transaction costs that we obtained are comparable to those obtained by Lesmond, Chen and Wei (2005), who use daily corporate bond quotes obtained from Datastream.



Figure 1: Latent liquidity rating as a function of bond age: This figure presents the pattern of changes in the average latent liquidity with respect to age of bond (in years), for trades in US corporate dollar-denominated bonds, in the State Street Corporation custody trades database, during the period 2000- 2005. The latent liquidity of a bond is defined as the aggregate weighted-average level of turnover of the investors holding the bond. The age of a bond is defined as the number of years since issue. The values of the latent liquidity rank vary between 0 and 1, where 0 represents the lowest liquidity level and 1 the highest liquidity level.



Figure 2: Latent liquidity rating as a function of issue size: This figure presents the pattern of changes in the average latent liquidity with respect to issue size (in billions of US Dollars), for trades in US corporate dollar-denominated bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The latent liquidity of a bond is defined as the aggregate weighted-average level of turnover of the investors holding the bond. he values of the latent liquidity rank vary between 0 and 1, where 0 represents the lowest liquidity level and 1 the highest liquidity level. Issue size is defined as the amount of principal at issuance.



Figure 3: Latent liquidity as a function of maturity: This figure presents the pattern of changes in the average latent liquidity with respect to time to maturity (in years), for trades in US corporate dollar-denominated bonds, in the State Street Corporation custody trades database, during the period 2000- 2005.The latent liquidity of a bond is defined as the aggregate weighted-average level of turnover of the investors holding the bond. The age of a bond is defined as the number of years since the issue date. The values of the latent liquidity rating vary between 0 and 1, where 0 represents the lowest liquidity level and 1 the highest liquidity level.



Figure 4: Latent liquidity as a function of coupon: This figure presents the pattern of changes in the average latent liquidity with respect to coupon (in %) for trades in US corporate dollar-denominated bonds, in the State Street Corporation custody trades database database, during the period 2000-2005. The latent liquidity of a bond is defined as the aggregate weighted-average level of turnover of the investors holding the bond. The coupon is defined as the annual payment in relation to the principal amount of the bond. The values of the latent liquidity rank vary between 0 and 1, where 0 represents the lowest liquidity level and 1 the highest liquidity level.



Figure 5: Latent liquidity as a function of Moody's Ratings Categories: This figure gives the average value of latent liquidity for various Moodys credit rating categories, in US corporate dollar-denominated bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The latent liquidity of a bond is defined as the aggregate weighted-average level of turnover of the investors holding the bond. The values of the latent liquidity rank vary between 0 and 1, where 0 represents the lowest liquidity level and 1 the highest liquidity level.

Table 1-A: Composition of bonds outstanding in the State Street Corporation custody database, by Industry: This table presents the composition, by industry category, as defined by Reuters, of dollardenominated US corporate bonds outstanding, as estimated by them, as of June 30, 2006. This aggregate amount accounts for about 97% of the total US corporate bonds outstanding of \$5,164.9 billion, based on the data of the Bond Market Association (BMA) at http://www.bondmarkets.com/story.asp?id=2455. The first column defines the eleven industry categories, and the second and third columns define the amounts in billions of US dollars, of the total holdings in the markets for the universe of all issues, and for those issues where State Street Corporation served as custodian. The third and fourth columns show the relative amounts in percent for the eleven industry categories in the Reuters and State Street databases, respectively. The last column indicates the relative amount held by State Street, as a fraction of total US dollar amounts outstanding, in each industry category.

	Total	<b>State Street</b>	Total	<b>State Street</b>	<b>State Street</b>
	Outstanding	Holdings	Outstanding	Holdings	Holdings
Industry			As $%$ Of	As $%$ Of	As $%$ Of
			Total	Total	<b>Total OS</b>
<b>Banks</b>	\$701	\$145	13.96	19.87	20.67
Consumer Goods	\$124	\$16	2.47	2.24	13.15
Electric Power	\$284	\$34	5.65	4.73	12.16
Energy Company	\$197	\$29	3.92	3.92	14.52
<b>Gas Distribution</b>	\$22	\$2	0.43	0.34	11.25
Independent Finance	\$ 35	$\$ 3$	0.69	0.45	9.38
Manufacturing	\$563	\$72	11.21	9.87	12.78
Other Financial	\$1,972	\$287	39.25	39.30	14.54
Service Company	\$620	\$92	12.34	12.61	14.84
Telephone	\$415	\$ 36	8.27	4.98	8.75
Transportation	\$91	\$12	1.81	1.71	13.69
Total	\$5,025	\$730	100	100	14.52

Table 1-B: Composition of bonds outstanding in the State Street Corporation custody database, by credit rating:This table presents the composition, by credit rating, as defined by Moodys, of dollardenominated US corporate bonds outstanding, as estimated by Reuters, as of May 31, 2006. This aggregate amount accounts for about 97% of the total US corporate bonds outstanding of \$5,164.9 billion, based on the data of the Bond Market Association (BMA) at http://www.bondmarkets.com/story.asp?id=2455. The first column defines the nine credit rating categories, and the second and third columns define the amounts in billions of US dollars, of the total holdings in the markets for the universe of all issues, and for those issues where State Street Corporation served as custodian. The third and fourth columns show the relative amounts in percent for the nine credit rating categories in the Reuters and State Street databases, respectively. The last column indicates the relative amount held by State Street, as a fraction of total US dollar amounts outstanding, in each credit rating category.

	Total	<b>State Street</b>	Total	<b>State Street</b>	<b>State Street</b>
	Outstanding	Holdings	Outstanding	Holdings	Holdings
Rating			As % Of	As % Of	As $%$ Of
			Total	Total	<b>Total OS</b>
Aaa	\$377	\$89	7.49	12.20	23.65
Aa	\$935	\$188	20.12	29.30	20.07
$\mathsf{A}$	\$1,161	\$125	24.97	19.46	10.74
Baa	\$905	\$119	19.47	18.59	13.16
Ba	\$549	\$60	11.82	9.42	10.99
B	\$379	\$73	8.15	11.35	19.20
Caa	\$126	\$17	2.70	2.70	13.76
Ca	\$81	\$4	1.75	0.61	4.77
$\mathcal{C}$	\$ 33	\$2	0.71	0.24	4.66
Other or NA Grade	\$479	\$53	10.30	8.34	11.16
Total	\$5,025	\$730	100	100	14.52

Table 1-C: Composition of bonds outstanding in the State Street Corporation custody database, by maturity: This table presents the composition, by maturity, of dollar-denominated US corporate bonds outstanding, as estimated by Reuters, as of June 30, 2006. This aggregate amount accounts for about 97% of the total US corporate bonds outstanding of \$5,164.9 billion, based on the data of the Bond Market Association (BMA) at http://www.bondmarkets.com/story.asp?id=2455. The first column defines the thirteen maturity categories, and the second and third columns define the amounts, in billions of dollars of the total holdings in the markets, for the universe of all issues, and for those issues where State Street Corporation served as custodian. The third and fourth columns show the relative amounts in percent for the thirteen maturity categories in the Reuters and State Street databases, respectively. The last column indicates the relative amount held by State Street, as a fraction of total US dollar amounts outstanding, in each maturity category.



Table 2: Comparision of trade volume between State Street Corporation custody compared to the whole market: This table presents statistics for the monthly traded volume (in billions of US dollars) of dollar-denominated US Corporate bonds for the entire market versus the amount traded in the State Street Corporations custody holdings database, during the period January 2004 to December 2005. Only securities greater than one year to maturity are considered. The aggregate market statistics is provided by Bond Market Association (BMA) at http://www.bondmarkets.com/story.asp?id=96. The first two columns indicate the date. The third and fourth columns indicate the average daily par quantity traded in the State Street database, and in the market, respectively. The last column indicates the ratio of the amount traded from State Street holdings to that for the entire market (expressed as a percentage).

Trade	Trade	Average Daily	Daily Average	Average Daily
Year	Month	Trade Volume	Trade Volume	Trade Volume
		in State Street	Market(in in	in State Street
		Custody Hold-	billions of US	Custody Hold-
		ings(in billions	Dollars)	ings(as a % of
		of US Dollars)		Market)
2004	January	$1.5\overline{3}$	25	$6.12\%$
2004	February	1.35	22	$6.13\%$
2004	March	1.78	22.7	7.84\%
2004	April	1.37	19.8	$6.92\%$
2004	May	1.30	18.4	7.05%
2004	June	1.24	20.1	6.18%
2004	July	1.42	20.6	$6.87\%$
2004	August	1.25	20.6	$6.08\%$
2004	September	1.47	21.1	$6.96\%$
2004	October	1.41	22.3	$6.30\%$
2004	November	1.42	22.7	6.25%
2004	December	1.21	19.4	$6.22\%$
2005	January	1.51	23	$6.55\%$
2005	February	1.37	21.9	$6.24\%$
2005	March	1.58	24.1	$6.56\%$
2005	April	1.32	20.5	$6.42\%$
2005	May	1.33	20.4	$6.52\%$
2005	June	1.39	21.8	$6.36\%$
2005	July	1.16	20.2	5.72%
2005	August	1.15	20.2	5.71%
2005	September	1.21	19.9	$6.08\%$
2005	October	1.13	20.7	5.45%
2005	November	1.16	19.8	5.84%
2005	December	1.06	19.6	$5.39\%$

Table 3: Trade distribution by the frequency of trading: This table presents statistics for the distribution of issues by frequency of trade, of US Corporate dollar denominated bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The frequency of trading of an issue is defined as number of distinct trading days in a given year. The data shows the number of issues corresponding to a particular trading frequency in each year. For example, in 2003, 5 issues traded more than 200 days and 42 issues traded between 150 and 200 days.

Frequency of Trading	2000	2001	2002	2003	2004	2005
$> 200$ days in year	$\theta$	$\overline{2}$	5	5	3	6
$150-200$ days in year	11	16	33	42	25	14
$100-150$ days in year	38	80	152	146	149	116
$50-100$ days in year	273	401	621	786	730	739
$30-50$ days in year	502	675	774	940	1007	961
$10-30$ days in year	1862	2169	2377	2439	2722	2672
5-10 days in year	1544	1716	1568	1754	1742	1580
At least 1 day and at most 5 days in year	6191	5866	4987	5006	4786	4335
No trade in year	7872	6979	7163	8262	8397	8693
Total Issues	18293	17904	17680	19380	19561	19116

Table 4: Trade distribution by industry sector: This table presents the distribution of trade market value, by industry sector, as defined by Reuters, of dollar-denominated US Corporate bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The trading distribution of a given industry sector is expressed as a percentage of total market value of trades, for the given year, within the State Street custody database.

<b>Industry Sector</b>	2000	2001	2002	2003	2004	2005
<b>Banks</b>	10	9	9	8	10	9
Telephone	13	12	9			
Manufacturing	15	14	14	17	15	15
Consumer Goods	3	3	4	4	3	2
Electric Power	4	6	5		6	6
Energy Company	6	5	6	5	5	5
Transportation	2	2	2		$\overline{2}$	
Other Financial	33	32	33	32	34	36
Service Company	15	16	17	19	17	18
Gas Distribution	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\mathbf{0}$	$\Omega$
Independent Finance	$\theta$					
Total	100	100	100	100	100	100

Table 5: Trading distribution by credit rating: This table presents the distribution of trade market value, by credit rating, as defined by Moodys of dollar-denominated US corporate bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The trading distribution of a given credit rating is expressed as percentage of total market value of trades, for the given year, within the State Streets custody trades database.

<b>Credit Rating</b>	2000	$\boldsymbol{2001}$	$\boldsymbol{2002}$	-2003	2004	2005
Aaa	2	3	4	4	4	3
Аa	12	12	12	11	13	14
А	38	38	30	24	25	21
Baa	23	28	30	29	26	29
Below Baa	24	20	24	33	31	34
Total	100	100	100	100	100	100

Table 6: Percentile distribution of trades, by maturity (in years): This table presents the distribution of maturity, in years, of trades in dollar-denominated US corporate bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The maturity of a bond is defined as the years remaining to maturity. Bonds that trade in a given year, are sorted in the order of increasing maturity, and the decile cutoff values are computed. The value shown is the maturity of the bond at the given percentile. For example, the data shows that the median trade had a time to maturity of 5.6 years in 2000 and 5.9 years in 2005.

Percentile	2000	2001	2002	2003	2004	2005
10	1.0	0.9	0.9	1.0	1.1	1.0
20	1.9	1.9	2.0	2.2	2.2	2.0
30	3.0	3.0	3.2	3.4	3.4	3.1
40	4.3	4.4	4.5	4.6	4.6	4.5
50	5.6	5.6	5.5	5.6	5.9	5.9
60	7.0	6.8	6.8	7.2	7.4	7.2
70	8.3	8.2	8.7	9.2	9.1	8.8
80	9.9	10.0	10.6	12.1	11.4	11.0
90	22.7	22.4	22.9	23.2	22.2	21.6

Table 7: Percentile distribution of trades, by age (in years): This table presents the distribution of age, in years, of trades in dollar-denominated US denominated bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The age of a bond is defined as the number of years since its issue. Bonds that trade in a given year, are sorted in the order of increasing age, and the decile cutoff values are computed. The value shown is the age of the bond at the given percentile. For example, the data shows that the median trade had an age of 2.5 years in 2000 and 2.3 years in 2005.

Percentile	<b>2000</b>	2001	2002	$\boldsymbol{2003}$	2004	2005
10	0.2	0.1	0.2	0.1	0.1	0.1
20	0.7	0.6	0.7	0.4	0.4	0.6
30	1.4	1.4	1.4	1.0	0.9	1.1
40	2.0	2.2	2.3	1.8	1.5	1.7
50	2.5	3.0	$3.3\,$	2.8	2.4	2.3
60	3.1	3.7	4.2	4.2	3.5	3.3
70	4.0	4.5	5.0	5.2	5.1	4.6
80	5.3	5.9	6.4	6.4	6.5	6.8
90	7.5	8.2	8.9	8.4	8.4	8.7

Table 8: Percentile distribution of trades, by face value outstanding (millions of US dollars): This table presents the distribution of face value (in millions of US Dollars) of trades in corporate-dollar denominated bonds, in the State Street Corporation custody trades database, during the period 2000-2005. The face value of a bond is defined as the amount outstanding on the trade date. Bonds that trade in a given year, are sorted in the order of increasing face amount and the decile cutoff values are computed. The value shown is the average face value of the bond for the given percentile. For example, the data shows that the median trade had a face value of 175 million dollars in 2000 and 250 million dollars in 2005.

Percentile	2000	2001	2002	2003	2004	2005
10	25	43	64	76	90	100
20	71	100	100	120	125	150
30	100	125	150	150	165	195
40	149	150	195	200	200	220
50	175	200	215	250	250	250
60	200	250	260	300	300	300
70	259	300	315	350	375	400
80	350	400	483	500	500	500
90	500	605	701	750	750	800

Table 9: Percentile distribution of trades, by time elapsed between successive trades (in days): This table presents the distribution of time elapsed between trades (in days) of trades in dollar-denominated US corporate bonds, in the State Street Corporation custody trades database during the period 2000-2005. The time elapsed is defined as the number of days between successive trades of a given bond. Bonds that trade in a given year, are sorted in the order of increasing time elapsed and the decile cutoff values are computed. The values shown are the average time elapsed of the bond for the given percentile range. For example, the data shows that the median trade had a elapsed time of 14 days in 2000 between successive trades and 12 days in 2005.

Percentile	<b>2000</b>	2001	2002	2003	2004	2005
10						
20	3	3	3	2	2	2
30	6		6	4	4	4
40	9	13	10		8	8
50	14	22	18	13	13	12
60	21	35	31	24	23	21
70	30	56	54	42	40	39
80	44	93	100	82	79	78
90	77	171	206	184	187	188

Table 10: Correlation between various Liquidity Measures: This table presents the correlation between the various measures of liquidity. The measures of liquidity are latent liquidity, trade days, trade count and traded market value. Each of the the measures is expressed as a percentile. These variables are calculated from a set of dollar-denominated US corporate bonds, that traded at least once during a calendar year, in the State Street Corporation custody trades database. To calculate the latent liquidity percentile, latent liquidity values are identified as of first trade date of year. These values are arranged in increasing order, for a given year and a percentile number is calculated. A higher latent liquidity percentile value indicates higher liquidity. To calculate the number of trade days percentile, we first divide the number of trades for the given issue in the given year, by the amount outstanding as of the first trade day for that year. These normalized values are arranged in increasing order, for a given year and a percentile number is calculated. A higher trade days percentile value indicates higher liquidity. To calculate the trade count percentile (the dependent variable), we first divide the number of trades for the given issue in the given year, by the amount outstanding as of the first trade day for that year. These normalized values are arranged in increasing order, for a given year and a percentile number is calculated. A higher trade count percentile value indicates higher liquidity. To calculate the trade market value percentile, we first divide the total market value of trades for the given issue in the given year, by the amount outstanding as of the first trade day for that year. These normalized values are arranged in increasing order, for a given year and a percentile number is calculated. A higher trade market value percentile value indicates higher liquidity.



Table 11: Random Effects Regressions for the drivers of liquidity: This table shows the result of random effects regressions using three different measures of liquidity on the sample of dollar-denominated US corporate bonds consisting of the State Street custody database from January, 2000 to June, 2006. All variables are measured at a quarterly frequency. The liquidity variables used are the latent liquidity of the bond at the beginning of the quarter, the number of trades in a given bond in a quarter, and the quarterly volume of trading in terms of market value. The trading volume and trade count measures used here are based on information available from the database of State Street holdings, since there is no trading information available on TRACE prior to July, 2002. Ratings are based on the Moody's classification scheme represented as a cardinal scale: Aaa-1 Aa-2 A-3 Baa-4 and below Baa - 5. The liquidity variables are represented in terms of percentile values. In order to compute percentile values, we rank the bonds for each quarter in terms of the liquidity measures and divide by the number of bonds for which information is available for that measure for that particular quarter. Maturity dummies represent whether the bond had an original maturity of 5 years, 7 years, 10 years or 30 years. The remaining variables are self-explanatory. The regressions take the form of random effect regressions with the quarter for which the liquidity is measured as the grouping variable. This is done so as to account for the fact that residuals within each quarter may be correlated across bonds. We use clustered standard errors, where the clustering is done by quarter.



Table 12: Fama-Macbeth regressions for the drivers of Liquidity: This table shows the result of Fama-Macbeth regressions using three different measures of liquidity using three different measures of liquidity on the sample of bonds consisting of the State Street Corporation custody database from January, 2000 to June, 2006. All variables are measured at a quarterly frequency. The liquidity variables used are the latent liquidity of the bond at the beginning of the quarter, the number of trades in a given bond in a quarter, and the quarterly volume of trading in terms of market value. The trading volume and trade count measures used here are based on information available from the database of State Street holdings, since there is no trading information available on TRACE prior to July, 2002. Ratings are based on the Moody's classification scheme represented as a cardinal scale: Aaa-1 Aa-2 A-3 Baa-4 and below Baa - 5. The liquidity variables are represented in terms of percentile values. In order to compute percentile values, we rank the bonds for each quarter in terms of the liquidity measures and divide by the number of bonds for which information is available for that measure for that particular quarter. Maturity dummies represent whether the bond had an original maturity of 5 years, 7 years, 10 years or 30 years. The remaining variables are self-explanatory. The regressions take the form of Fama-Macbeth regressions with the quarter for which the liquidity is measured as the grouping variable. This is done so as to account for the fact that residuals within each bond may be correlated across quarters.



Table 13: Significance of coefficients in Fama-Macbeth regressions: This table shows the relative number of positive, positive significant (at the 5% level), negative and negative significant coefficients that result in Fama-Macbeth regressions reported in table 12, using three different measures of liquidity on the sample of bonds consisting of the State Street Corporation custody database from January, 2000 to June, 2006. All variables are measured at a quarterly frequency. The liquidity variables used are the latent liquidity of the bond at the beginning of the quarter, the number of trades in a given bond in a quarter, and the quarterly volume of trading in terms of market value. The trading volume and trade count measures used here are based on information available from the database of State Street holdings, since there is no trading information available on TRACE prior to July, 2002. Ratings are based on the Moody's classification scheme represented as a cardinal scale: Aaa-1 Aa-2 A-3 Baa-4 and below Baa - 5. The liquidity variables are represented in terms of percentile values. In order to compute percentile values, we rank the bonds for each quarter in terms of the liquidity measures and divide by the number of bonds for which information is available for that measure for that particular quarter. Maturity dummies represent whether the bond had an original maturity of 5 years, 7 years, 10 years or 30 years. The remaining variables are self-explanatory. The regressions take the form of Fama-Macbeth regressions with the quarter for which the liquidity is measured as the grouping variable. This is done so as to account for the fact that residuals within each bond may be correlated across quarters.



Table 14: Univariate Regressions of Transactions costs and price impacts on Latent Liquidity: This table shows, quarter by quarter, univariate regressions of the transaction costs estimates and of Amihud's ILLIQ measure of price impact calculated using TRACE data for a given quarter for a bond and its percentile rank (from 0 to 1) on the basis of latent liquid. The transaction costs are estimated using a limited dependent variable model for every bond for every quarter using the 5 year interest rate and the return on the S&P index as benchmarks. The percentile rank of latent liquidity is computed by ranking bonds every month in terms of latent liquidity and then dividing the bonds by the number of bonds available for that month. The first rank is given to the lowest liquidity security. This gives us a measure that is comparable from month to month. The sample consists of bonds that are traded on TRACE for a minimum of five days every quarter, and for whom information on latent liquidity is available from the State Street Corporation holdings database. The time period covered is July 2002 to June 2006.

	Transaction costs ( $%$ of price)				Log(ILLIQ)	
	Latent Liquidity	Constant	R-squared	Latent Liquidity	Constant	R-squared
Q302	$-0.439$ (1.22)	0.469 (1.74)	0.01	$-1.998$ $(2.11)^*$	$-10.988$ $(15.72)$ **	0.02
Q402	$-0.953$ $(2.24)^*$	0.858 $(2.65)$ **	0.02	1.136 (1.44)	$-13.018$ $(21.69)$ **	0.01
Q103	$-0.608$ $(2.60)$ **	0.946 $(6.37)$ **	0.01	$-4.087$ $(9.44)$ **	$-8.916$ $(32.86)$ **	0.13
Q203	$-1.422$ $(4.24)$ **	1.686 $(8.09)$ **	0.03	$-3.599$ $(9.60)$ **	$-9.207$ $(39.57)$ **	0.12
Q303	$-2.059$ $(5.95)$ **	2.103 $(10.14)$ **	0.05	$-3.394$ $(9.29)$ **	$-9.271$ $(42.52)$ **	0.11
Q403	$-2.217$ $(6.15)$ **	2.209 $(10.43)$ **	0.05	$-2.979$ $(8.73)$ **	$-9.448$ $(47.21)$ **	0.09
Q104	$-2.303$ $(6.48)$ **	2.065 $(10.31)$ **	0.05	$-3.745$ $(8.88)$ **	$-9.499$ $(39.91)$ **	0.09
Q204	$-2.617$ $(6.73)$ **	2.367 $(10.57)$ **	0.05	$-4.209$ $(10.22)$ **	$-9.136$ $(38.71)$ **	0.11
Q304	$-2.530$ $(6.17)$ **	2.452 $(10.18)$ **	0.04	$-3.114$ $(7.46)$ **	$-9.901$ $(40.14)$ **	0.06
Q404	$-2.801$ $(9.84)$ **	2.971 $(16.82)$ **	0.06	$-1.994$ $(7.56)$ **	$-10.131$ $(62.39)$ **	0.03
Q105	$-2.232$ $(7.11)$ **	2.934 $(14.74)$ **	0.03	$-1.129$ $(4.23)$ **	$-10.667$ $(63.05)$ **	0.01
Q205	$-2.235$ $(6.19)$ **	2.906 $(12.53)$ **	0.03	$-1.350$ $(5.41)$ **	$-10.237$ $(63.90)$ **	0.02
Q305	$-2.284$ $(6.53)$ **	2.950 $(13.03)$ **	0.03	$-1.581$ $(6.12)$ **	$-10.196$ $(60.94)$ **	0.03
Q405	$-1.898$ $(5.19)$ **	2.680 $(11.38)$ **	$\rm 0.02$	$-1.224$ $(4.40)$ **	$-10.290$ $(57.53)$ **	0.01
Q106	$-3.016$ $(7.08)$ **	3.284 $(11.62)$ **	0.04	$-1.514$ $(4.77)^{**}$	$-10.265$ $(48.69)$ **	0.02
Q206	$-2.240$ $(5.40)$ **	2.916 $(10.49)$ **	0.02	$-1.694$ $(5.49)$ **	$-9.998$ $(48.32)$ **	0.03
Overall	$-2.024$ $(21.24)$ **	2.460 $(40.91)$ **	0.03	$-2.171$ $(25.82)$ **	$-9.977$ $(188.51)$ **	0.04
	Robust t statistics in parentheses					
	* significant at 5%; ** significant at $1\%$					

maturity. The transaction costs are estimated using a limited dependent variable model for every bond for every quarter using the 5 year interest rate Table 15: Transactions costs, liquidity and bond characteristics: This table shows, quarter by quarter, the relationship between the transaction on latent liquidity for that quarter and the average number of trades in the bond during that quarter and two other bond characteristics: coupon and and the return on the S&P index as benchmarks. The normalized rank is computed by ranking bonds every month in terms of latent liquidity and then dividing the bonds by the number of bonds available for that month. The first rank is given to the lowest liquidity security. This gives us a measure that is comparable from month to month. The sample consists of bonds that are traded on TRACE for a minimum of five days every quarter, and for whom information on latent liquidity is available from the State Street Corporation custody holdings database. The time period covered is July 2002 to June costs in  $%$  estimated from trade data for a given quarter for a bond and two liquidity-related variables: the bond's percentile rank (from 0 to 1) based Table 15: Transactions costs, liquidity and bond characteristics: This table shows, quarter by quarter, the relationship between the transaction costs in % estimated from trade data for a given quarter for a bond and two liquidity-related variables: the bond's percentile rank (from 0 to 1) based on latent liquidity for that quarter and the average number of trades in the bond during that quarter and two other bond characteristics: coupon and maturity. The transaction costs are estimated using a limited dependent variable model for every bond for every quarter using the 5 year interest rate and the return on the S&P index as benchmarks. The normalized rank is computed by ranking bonds every month in terms of latent liquidity and then dividing the bonds by the number of bonds available for that month. The first rank is given to the lowest liquidity security. This gives us a measure that is comparable from month to month. The sample consists of bonds that are traded on TRACE for a minimum of five days every quarter, and for whom information on latent liquidity is available from the State Street Corporation custody holdings database. The time period covered is July 2002 to June 2006.



measure is computed quarterly using daily returns and trading volumes in each bond. The percentile rank is computed by ranking bonds every month<br>in terms of latent liquidity and then dividing the bonds by the number of bon collarly: This gives us a measure once is comparant morm to morning the state Street Corporation custody holdings database. The time period covered is July 2002 to June 2006. security. This gives us a measure that is comparable from month to month. The sample consists of bonds that are traded on TRACE for a minimum of measure calculated using daily TRACE data for a given quarter for a bond and two liquidity-related variables: the bond's percentile rank (from 0 to 1) based on latent liquidity for that quarter and the average number of trades in the bond during that quarter, and other bond characteristics. The ILLIQ security. This gives us a measure that is comparable from month to month. The sample consists of bonds that are traded on TRACE for a minimum of Table 17: Price Impact, Liquidity and Bond Characteristics: This table shows, quarter by quarter, the relationship between Amihud's ILLIQ Table 17: Price Impact, Liquidity and Bond Characteristics: This table shows, quarter by quarter, the relationship between Amihud's ILLIQ measure calculated using daily TRACE data for a given quarter for a bond and two liquidity-related variables: the bond's percentile rank (from 0 to 1) based on latent liquidity for that quarter and the average number of trades in the bond during that quarter, and other bond characteristics. The ILLIQ measure is computed quarterly using daily returns and trading volumes in each bond. The percentile rank is computed by ranking bonds every month in terms of latent liquidity and then dividing the bonds by the number of bonds available for that month. The first rank is given to the lowest liquidity five days every quarter, and for whom information on latent liquidity is available from the State Street Corporation custody holdings database. The time period covered is July 2002 to June 2006.

