Corporate Bond Market Transparency and Transaction Costs

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Abstract

Using TRACE data—a complete record of all US OTC secondary trades in corporate bonds—we estimate average transaction cost as a function of trade size for each bond that traded more than nine times in 2003. We find that transaction costs are higher than in equities and decrease significantly with trade size. Highly rated bonds, recently issued bonds, and bonds that will soon mature have lower transaction costs than do other bonds. Costs are lower for bonds with publicly disseminated trade prices, and they drop when the TRACE system starts to publicly disseminate their prices. The results suggest that public traders would significantly benefit if bond prices were made more transparent.

Keywords: Corporate bonds, fixed income, liquidity, transaction cost measurement, effective spreads, TRACE, price transparency, market microstructure, dealers.

Corporate Bond Market Transparency and Transaction Costs

Secondary trading costs in the corporate bond markets are not widely known outside of the community of professional fixed income traders. Given the importance of bond financing in our economy—the aggregate values of corporate bonds and equities are roughly equal in the US—it is somewhat surprising that so little is known about the costs of trading bonds. This study characterizes these costs using a record of every corporate bond trade reported in 2003.

Bond trading costs are not well known because corporate bond markets are not nearly as transparent as are equity markets. Dealers provide public quotes for few bonds on a continuous basis, and until recently, most bond transaction prices have never been published. We study whether this lack of price transparency contributes to bond transaction costs, which we find to be substantially higher than equity transaction costs.

Our results have implications for investors, issuers, and regulators. Investors incorporate transactions costs into their portfolio decisions. Their investment decisions depend on the costs of investing in bonds as well as the costs of divesting from them should they require liquidity before their bonds mature. Issuers consider secondary market transactions costs when deciding how to structure their bonds. Bond features that reduce liquidity are unattractive to investors and therefore costly to issuers.[1] Regulators study transaction costs to determine how they depend on market structure, and in particular, on price transparency. Understanding such relations allows them to adopt regulatory polices to better promote competition and efficiency.

US bond markets are becoming increasingly transparent. The National Association of Securities Dealers (NASD) now requires dealers to report all OTC bond transactions through its TRACE (Trade Reporting and Compliance Engine) bond price reporting system. This system became operational on July 1, 2002. Under pressure from Congress, buy-side traders and the SEC, the NASD is phasing-in real time dissemination of these prices to the public. As of the end of 2003, The TRACE system disseminates bond prices no later than 45 minutes after trades occur in about one-half of all traded bond issues. The Bond Market Association, the trade organization for bond dealers, questions whether all bonds should be transparent, citing concerns

[1] Amihud and Mendelson (1991) find that bond liquidity influences yield to maturity and, therefore, issuers cost of capital.

that transparency will hurt liquidity.[2] The results of this study should help inform the debate over the effect of transparency on liquidity. We find that trading costs are lower for transparent bonds than for similar opaque bonds, and that these costs fall when a bond's prices are made transparent. We interpret these results as evidence that transparency has improved liquidity in corporate bond markets.

Our cross-sectional and time-series estimates suggest that transparency decreases customer transaction costs by roughly five basis points and probably more. Our data shows that in 2003, public investors traded approximately two trillion dollars in bond issues for which prices were not published on a contemporaneous basis. These results suggest that investors may save a minimum of one billion dollars per year if the prices of all bonds were made TRACE-transparent with the existing 45-minute reporting protocol. This figure represents a lower bound on the cost savings because learning how to obtain, organize, and use price data takes time. For example, most traders now do not—indeed cannot—obtain last trade prices from their brokers at the time they submit their orders. Accordingly, we will not observe the full effect of transparency on transaction costs immediately after prices have been made more transparent. Since our cost savings estimate is based on information about transaction costs that was collected while traders were still learning about the availability of price data, we undoubtedly have underestimated the ultimate total cost savings.

The discussion proceeds as follows. Section 1 reviews the related literature. Section 2 describes our data and sample selection procedures and presents final sample characteristics. Section 3 describes the methods we use to estimate average bond transaction costs. Sections 4 and 5 respectively present time-series and cross-sectional results based on these methods. Section 6 introduces the method we use to estimate time varying transaction costs for a set of bonds and shows that transaction costs substantially dropped in bonds that became TRACE-transparent during our sample period. Finally, Section 7 concludes and discusses the importance of the results in the context of current regulatory initiatives.

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[2] See, for example, "Testimony before The Committee on Banking, Housing and Urban Affairs, United States Senate," Statement of Micah S. Green, President, The Bond Market Association, June 17, 2004 Oversight Hearing on Bond Market Regulation.

1. Related Literature

The academic literature considers price transparency to be an important determinant of the liquidity of securities. For example, see O'Hara (1997) and Madhavan (2000) for a survey. Some market practitioners complain that price transparency could hurt the liquidity of corporate bonds. No published study of which we are aware comprehensively and directly examines how introducing price transparency affects corporate bond liquidity. Our study attempts to fill this gap.

Our study uses the most comprehensive source of transaction data for corporate bond transactions in the United States. We use transaction data from the NASD's TRACE system. The TRACE data consist of all over-the-counter (OTC) transactions in all corporate bonds. Earlier researchers studied datasets that only include transactions made by some large buy-side institutions (e.g., Capital Access International) or transactions for a subset of bonds (e.g., Fixed Income Pricing System).[3]

Our study applies and extends the Harris and Piwowar (2004) transaction cost estimation methods, developed for their study of secondary trading costs of municipal bonds, to corporate bonds. Their econometric time-series transaction cost model is appropriate for the OTC corporate bond market because it shares many of the same features with the municipal bond market: corporate bond dealers do not post firm bid and ask quotes; corporate bond transaction data include an indicator of whether the trade was a dealer sale to a customer, a dealer purchase from a customer, or an interdealer transaction; and many corporate bond issues trade very infrequently. We extend their methods by allowing liquidity to be time varying. This extension allows us to examine how the introduction of price transparency affects corporate bond transaction costs.[4]

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[3] The Capital Access International (CAI), Fixed Income Securities Database (FISD), Datastream, NYSE Automated Bond System (ABS), and other voluntary or limited proprietary datasets tend to contain only a subset of the pricing information useful for many research questions. The CAI dataset, for example, contains only institutional trades that do not represent the full market very well. CAI transactions have a median trade size of $1.5 million (Schultz, 2001) to $4.4 million (Chakravarty and Sarkar, 2003) but we now know from the TRACE data that typical trade sizes in corporate bonds are actually around $30,000. Therefore, while the CAI dataset may prove quite useful for some research questions, it does not capture the overall market very well. Likewise, data from the Fixed Income Pricing System (FIPS) contains complete pricing information when combined with exchange transactions, but this information is available for only a small set of bonds. This limitation means that FIPS does not allow for broad cross-sectional analyses.

[4] Harris and Piwowar (2004) could not directly test the effects of price transparency on liquidity in the municipal bond market because bond prices during their sample period were published in this market only if the bond traded four or more times. As a result, they could not disentangle transparency effects from trading activity effects.

Our transaction cost estimation methods differ significantly from those used in earlier studies of corporate bond trading costs. Previous studies of corporate bond transaction costs have employed two main approaches. The first approach, used by Hong and Warga (2000), Chakravarty and Sarkar (2003) and others, computes same-bond-same-day effective spreads.[5] This approach compares the average price of buy transactions to sell transactions on the same day. The requirement of at least one buy and one sell on the same day is extremely limiting in corporate bonds, because the median number of trades per day is less than one. This approach eliminates most transactions when estimating bond transaction costs for most bonds, and it cannot estimate transaction costs for many infrequently traded bonds. This type of estimator thus is not well suited for inactively traded securities, and therefore, for use in broad cross-sectional analyses.

The second approach is a regression-based methodology. Schultz (2001) compares each transaction price to a benchmark price and regresses the difference on a buy/sell indicator. The coefficient on the buy/sell indicator estimates the transaction costs. His regression approach offers an improvement over the same-bond-same-day effective spread because it can measure transaction costs for inactive bonds as well as active bonds. However, Schultz (2001) admits that this method does not work particularly well for high-yield bonds because the benchmark is more difficult to estimate.

Chen, Lesmond, and Wei (2002) propose a different regression approach by extending Lesmond, Ogden, and Trzcinka (1999). Their approach assumes that a zero return day (or a non-trading day) is observed when the true price changes by less than the transaction costs. Using this assumption and applying a two-factor return-generating model, Chen et al (2002) estimate transaction costs.[6] Unlike the Schultz (2001) regression approach, the Chen et al regression approach uses only end-of-day transaction prices and no buy-sell indicators. Because many corporate bonds are inactive, observed end of day prices may represent trades early in the day. Further, a non-trading day in corporate bonds may not necessarily reflect transaction costs

[5] See also Green, Hollifield, and Schürhoff (2004) and Kalimpalli and Warga (2002).
[6] As factors, Chen et al. (2002) use changes in the interest rate, which are important for investment grade bonds, and returns on the S&P 500 index, which are important for high-yield bonds.

because corporate bonds tend to have close substitutes, and because many bonds are so infrequently traded that on most days nobody even considers trading them.[7]

Our transparency and cross-sectional analyses are related to previous work in bond market microstructure. Alexander, Edwards, and Ferri (2000) find that transparent high yield bonds can be fairly liquid. We show that transparent bonds have lower transaction costs than nontransparent bonds, and that transaction costs drop when bonds become price transparent.

We examine the effect of credit risk on the corporate bond transaction costs. Previous studies have examined the effect of credit risk on volume, yield, volatility, and spread but the results are mixed. For investment grade corporate bonds, Chakravarty and Sarkar (2003) and Hong and Warga (2000) find that same-bond-same-day spreads increase with credit risk, but Schultz (2001) finds no liquidity pattern associated with credit risk. Alexander, Edwards, and Ferri (2000) finds that high-yield bonds with more credit risk have higher trading volume than high-yield bonds with lower credit risk. Chen et al (2002) examine credit risk across both high-yield and investment grade corporate bonds, but their results are mixed at best. For municipal bonds, Downing and Zhang (2004) find increases in volatility with more credit risk and Harris and Piwowar (2004) find that bonds with higher credit risk are more expensive to trade. We find that secondary corporate bond transaction costs increase with credit risk.

2. Data and Sample

We obtain reports of every corporate bond trade reported to TRACE for 2003 (252 trading days) from the NASD. Our TRACE data set contains reports of all OTC trades in all corporate bonds.[8] Data items include the price, time, and size of the transaction as well as the side (or sides for interdealer transactions) on which the dealer participated. We also have issuer and issue information provided by TRACE master files in the form of five snapshots taken during the sample period.

The only trades omitted from TRACE are those that occurred on exchanges, of which the vast majority occur on in the NYSE's Automated Bond System (ABS). Fewer than five percent of all bonds are listed on the NYSE. For those bonds, ABS trades, which are almost all small

[7] These two problems are exaggerated in the Chen et al. (2002) estimation because the data they study contains only transactions reported by one large bond dealer. Because the Chen et al (2002) sample period occurs before bond market transparency, the large bond dealer could only have observed a subset of trades. Therefore, the end-of-day prices are more likely to occur early in the day and the observed zero-return days may not really be zero-return days.
[8] Note that our data set contains all trades reported to TRACE, whether disseminated or not.

retail trades, represent from 0 to 40 percent of all transactions. The TRACE dataset thus is very nearly a complete record of all corporate bond trades.

The NASD started collecting the TRACE dataset on July 1, 2002. Our analysis uses 2003 data to allow market participants to familiarize themselves with the system.

The 2003 TRACE data identifies almost 70,000 securities in which dealers must report their trades. Dealers made 8.7 million trade reports representing total volume of 9.4 trillion dollars in only 22,453 of these securities. The remainder of these securities did not trade in 2003. The TRACE master files classify the majority of these bonds as "inactive" issues.

We analyze all trade reports except those that subsequently were corrected, those for which we suspect the data were incorrectly reported,[9] those for which data are missing, those in bonds for which the total number of trades reported is insufficient to identify the regression model that we use to estimate transaction costs,[10] and duplicate interdealer trade reports. The final sample includes 6,649,758 trades in 16,746 bonds representing 5.0 trillion dollars of volume. The reductions in total trades, total volume and numbers of bonds are respectively due mostly to duplicate interdealer reports, corrected trades, and unidentified regressions. Table 1 provides a complete breakdown of the effects of these filters on the final sample.

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[9] Filtering for data errors in corporate bonds is somewhat more difficult than in equities because prices for many bonds are observed so infrequently. A large price change filter thus may identify situations where prices changed substantially between transactions that occurred weeks apart. To avoid this problem, we designed two types of filters that operated on deviations from median prices and price reversals. In particular, we first applied the median filter. Because corporate bond prices can change drastically with new company information, we first examined the bonds that did not seem to experience the large price changes and deleted any trades with prices that deviate from the daily median by more than 10%. For the bonds that did experience price changes, we deleted any trades with prices that deviate more than 10% from a nine-trading-day median centered on the trading date. These median filters eliminate the most obvious pricing errors. Next, we estimate the percentage differences between the transaction price and last transaction price and between the transaction price and the next transaction price. We delete a transaction if the transaction price is different from the lead, lag, and average lead/lag by at least 10%. Because dealers may make the same clerical error more than once, we next estimate dealer prices by averaging the prices of consecutive trades by the same dealer. As with the transaction prices, we find the percentage difference between the dealer price and the lead dealer price and the lag dealer price and then we find the average of the two differences. If the dealer price is at least 10% different from the lead, lag, and average lead/lag dealer prices, we deleted it. Finally, we deleted the first (last) trade print in a bond if it was different than both the lead (lag) transaction price and the lead (lag) dealer price by at least 10%. Using this price-change filtering technique, we delete 38,009 transactions or 0.5% of transactions. We also filter out transactions with a recorded size that is not an integer, an execution date prior to the "First Active Date", an execution date after the maturity date or a recorded size greater than half of the total issue size.

[10] Since identification requires at least eight observations, all bonds in the remaining sample have at least nine observations. However, some bonds that traded nine or more times do not appear in our sample because their cost regressions were not identified. For example, if all reported trades for a bond were purchases, the cost regression would not be identified.

The median issuer in the sample only has two bond issues outstanding. This distribution, like most cross-sectional distributions, is skewed to the right: The average number of issues outstanding per issuer is more than seven. The average original issue size is $236 million and the average issuer has about $1.7 billion total outstanding. Bonds had an average of 12.1 years to maturity at issuance and have been around for 3.5 years on average. The average coupon in the sample is 6.3 percent and the average bond price in the sample is 100.4 percent of par.

Table 2 provides additional descriptive statistics for our sample. On average, bonds traded only 1.9 times per day. The median trade rate, however, was only 0.6 times per day. Trades were also clustered. The median bond traded only on 23 percent of all days in the sample. The total number of dealers reporting trades also varied substantially across bonds. The sample median is 22 dealers.

Perhaps the most surprising statistic is that the turnover in the sample is much higher than we expected. These results, however, are consistent with turnover results reported in Alexander, Edwards, and Ferri (2000). The sample median turnover is 52 percent and the average is 83 percent. More than 60 percent of the customer trades are in retail-sized transactions (less than 100,000 dollars) though most dollar volume, of course, is in institutional-sized trades.

2.1 Bond Classifications

Our cross-sectional analyses explore how bond transaction costs depend on trade frequency, credit quality, bond complexity, issue size, time since issuance, and time to maturity. To provide context for the results, we characterize these bond characteristics in this subsection, which briefly discusses statistics presented in Table 3.

The NASD added bonds to the TRACE-transparent price dissemination list on four days in 2003. Accordingly, some bonds were TRACE-transparent for only a portion of the year. For our cross-sectional regression analyses, we measure the degree to which trading was TRACE-transparent for each bond by the fraction of trades that were TRACE-transparent. Of the bonds in the sample, 22 percent were TRACE-transparent at some point in 2003. These bonds represent 49 percent of all trades and 53 percent of all dollar volume.

Trading on the NYSE's Automated Bond System (ABS) is completely price- and order-transparent. Our TRACE sample includes 444 bonds trading on ABS. TRACE reported trades in these bonds represent 4.6 percent of our sample and 3.4 percent of the total dollar volume. A small number of bonds are both TRACE transparent and ABS listed, but the majority of bonds, 48 percent of the trades, and 45 percent of the dollar volume were not transparent at all.

Our five snapshots of the TRACE master files include credit ratings for almost each bond from S&P and Moody's. After reviewing descriptions of the bond ratings, we assign their ratings to a common numeric scale that ranged from one for bonds in default to 25 for AAA bonds. We use the average rating across agencies and snapshots to quantify credit quality for each bond, after adjusting for average differences among the agencies in their ratings.[11]

For illustrative purposes, we classify each bond into four grades based on its average ratings: Superior (AA and above), all other investment grade (BBB to A), speculative grade (below BBB), and in default. The superior category includes 9 percent of the bonds, 7 percent of the trades, and 8 percent of the total value trade in the sample. Most of the remainder appears in the other investment grade category. Speculative grade bonds represent 23 percent of the bonds in the sample, 26 percent of the trades, and 31 percent of the volume. Unfortunately, we could not obtain a credit rating for a non-trivial percentage of our sample bonds. These bonds represent about 3 percent of the bonds in the sample, but only 1 percent of the number of trades and 2 percent of the total value traded. Three percent of the sample bonds were in default at some point during 2003.

We also classify bonds into three issue size categories. Almost half of the bonds in the sample fall into the medium ($100 million - $500 million) issue size category. Small bond issue sizes (less than $100 million) account for 40 percent of the number of sample bonds, but only 13 percent and 1 percent of the number of trades and the total value traded, respectively. Large bond issue sizes (greater than $500 million) account for only 14 percent of the number of sample bonds, but 53 percent and 67 percent of the number of trades and the total value traded, respectively.

The average age of the sample bonds is surprisingly low. Twenty percent of the bonds have an average age of less than 3 months. Most of the trades (51 percent) and volume (47 percent) occur in bonds aged between 1 year and ½ of the original time to maturity. As

[11] A simple average of these ratings could introduce unwanted variation into our results if some agencies awarded higher ratings than other agencies, or if our translation scheme does not accurately reflect equivalent credit risks. Without adjustment, the average for a bond could depend on which agency rated the bond. To remove this potential source of variation, we identified all bonds that both agencies rated. From that sample, we computed the mean difference between our numeric translations of their ratings. We then adjusted the Moody's rating by the mean

expected, bonds that are near the end of their life (28 percent of bonds) trade less frequently (23 percent of trades and 16 percent of volume) than do other bonds.

The TRACE master file identifies an industry for each bond based on the nature of the bond and not that of the issuer. For example, some Ford Motor Company bonds are classed as Finance bonds whereas others are classed as Industrial bonds. Companies from a wide array of industries issue bonds, but most bonds that trade are classified as Finance (49%) or Utilities (37%). Therefore, we divide the bonds into three industry categories, Finance, Utilities, and Other.

Some privately held companies issue publicly traded debt.[12] We identify public companies by matching the issuer's ticker symbol in TRACE to equity ticker symbols listed in the Center for Research in Security Prices dataset and on the OTC Bulletin Board (OTCBB) web site.[13] We then group subsidiaries of public companies with their parent. Some issuers may have publicly traded equity in other countries. We do not attempt to identify those but combine them with the private companies. In total, only 8.6 percent of the sample bonds are thus classified as private. Private companies are an even smaller percentage of trades (5 percent) and volume (7 percent). These totals are well below the percentage of private companies reported in Hotchkiss, Warga, and Jostova (2002). The discrepancy may be due to the problems of matching on CUSIP numbers.[14]

To characterize bond complexity in our sample, we identify bond features that complicate valuation analyses for investors. Callable bonds are redeemable by the issuer (in whole, or in part) before the scheduled maturity under specific conditions, at specified times, and at a stated price. About 34 percent of our sample bonds have call provisions. A small number of sample bonds (3 percent) have calls that are payable in something other than cash. Some bonds in the sample are putable (4 percent) and some are convertible (5 percent). Very few bonds have extendible maturities or are paid in kind.

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difference between the Moody's and S&P ratings and found the average of the S&P rating and the adjusted Moody's rating for each bond.

[12] A privately held company can issue public debt if it meets disclosure requirements similar to public companies.

[13] Only reporting companies (i.e., public companies) can trade on the OTCBB.

[14] Because different units of the same company can issue debt, the debt and equity do not match well using six digit CUSIP numbers.

Corporate bonds have coupons of many types. We classify types into fixed, floating, or variable. Floating coupons adjust to some index. Variable coupons adjust to some schedule. The floating and variable categories make pricing more complex.

A sinking fund provision requires the issuer to retire a specified portion of debt each year by repurchasing it on the open market. About 2 percent of our sample bonds have sinking fund provisions. Nonstandard interest payment frequency bonds pay interest at frequencies other than semiannual. About 21 percent of our sample bonds have nonstandard interest payment frequencies. Nonstandard interest accrual basis bonds do not accrue interest on a 30/360 capital appreciation basis. About 5 percent of our sample bonds have nonstandard interest accrual methods.

3. Average Bond Transaction Cost Estimation Methods

The TRACE data present two serious problems that transaction cost measurement methods must address. First, since quotation data generally does not exist for most of the corporate bond market, we cannot estimate transaction costs for each trade using standard transaction methods such as the effective spread that are based on benchmark prices. Instead, we estimate transaction costs using an econometric model.

The second problem is due to the scarcity of data for many bonds. Since our econometric model does not benefit from information in contemporaneous observable benchmark prices, our results are less precise than they would be if such information were available. We therefore carefully specify our model to maximize the information that we can extract from small samples, and we pay close attention to the uncertainties in our transaction cost estimates.

3.1 The Time-Series Estimation Model

We estimate transaction costs using the econometric model developed in Harris and Piwowar (2004). To conserve space, we only briefly describe the Harris and Piwowar model here.

Harris and Piwowar assume that the price of trade t, P_t, is equal to the unobserved "true value" of the bond at the time of the trade, V_t, plus or minus a price concession that depends on whether the trade initiator is a buyer or seller. The model separately estimates the sizes of these price concessions for customer trades and for interdealer trades.

The absolute customer transaction cost, $c(S_t)$, measured as a fraction of price, depends on the dollar size of the trade, S_t. The model analyzes relative transaction costs (cost as a fraction of price) and total dollar trade value because these are the only quantities that ultimately interest traders. We specify a functional form for $c(S_t)$ below.

Harris and Piwowar model the percentage price concession associated with interdealer trades by δ_t, which they assume is random with zero mean and variance given by σ_δ^2. If the interdealer trades are equally likely to be buyer-initiated as seller-initiated, the standard deviation σ_δ is proportional to the average absolute interdealer price concession.

Using Q_t to indicate with a value of 1, –1, or 0 whether the customer was a buyer, a seller, or not present (interdealer trade), and I_t^D to indicate with a value 1 or 0 whether the trade is an interdealer trade or not gives

(1) $$P_t = V_t + Q_t P_t c(S_t) + I_t^D P_t \delta_t = V_t \left(1 + \frac{Q_t P_t c(S_t) + I_t^D P_t \delta_t}{V_t} \right).$$

Taking logs of both sides and making two small approximations gives

(2) $$\ln P_t \approx \ln V_t + Q_t c(S_t) + I_t^D \delta_t .$$

Subtracting the same expression for trade *s* and dropping the approximation sign yields

(3) $$r_{ts}^P = r_{ts}^V + Q_t c(S_t) - Q_s c(S_s) + I_t^D \delta_t - I_s^D \delta_s$$

where r_{ts}^P and r_{ts}^V are respectively the continuously compounded bond price and "true value" returns between trades *t* and *s*.

Following Harris and Piwowar, we model the "true value" return r_{ts}^V by decomposing it into the linear sum of a time drift, an average bond index return, differences between index returns for long and short term bonds and for high and low quality bonds, and a bond-specific valuation factor, ε_{ts}.

(4) $$r_{ts}^V = Days_{ts}\left(5\% - CouponRate\right) + \beta_1 AveIndexRet_{ts} + \beta_2 DurationDif_{ts} + \beta_3 CreditDif_{ts} + \varepsilon_{ts}$$

where $Days_{ts}$ counts the number of calendar days between trades *t* and *s*, *CouponRate* is the bond coupon rate, $AveIndexRet_{ts}$ is the index return for the average bond between trades *t* and *s* and $DurationDif_{ts}$ and $CreditDif_{ts}$ are the corresponding differences between index returns for long and short term bonds and high and low quality bonds. The first term models the continuously compounded bond price return that traders expect when interest rates are constant and the bond's coupon interest rate differs from five percent.[15] The factor model accounts for bond value changes due to shifts in interest rates and credit spreads.[16] We estimate the bond indices using repeat sale regression methods with terms that account for bond transaction costs. Finally, the bond-specific valuation factor ε_{ts} has mean zero and variance given by

(5) $$\sigma^2_{\varepsilon_{ts}} = N^{Sessions}_{ts}\sigma^2_{Sessions}$$

where $N^{Sessions}_{ts}$ is the total number of trading sessions and fractions of trading sessions between trades *t* and *s*.

We model customer transaction costs using the following additive expression:

(6) $$c\left(S_t\right) = c_0 + c_1\frac{1}{S_t} + c_2\log S_t + c_3 S_t + c_4 S_t^2 + \kappa_t$$

where κ_t represents variation in the actual customer transaction cost that is unexplained by the average transaction cost function. This variation may be random or due to an inability of the average transaction cost function to well represent average trade costs for all trade sizes. We assume κ_t has zero mean and variance given by σ^2_κ.

The five terms of the cost function together define a response function curve that represents average trade costs. The following considerations motivated our choice of the terms in this function. The constant term allows total transaction costs to grow in proportion to size. It sets the level of the function. The second term characterizes any fixed costs per trade. The distribution of fixed costs over trade size is particularly important for small trades. The final three terms allow the costs per bond to vary by size, particularly for large trades. To obtain the most precise results possible, we also specified and estimated several other versions of the cost function. We discuss these alternatives and present their estimates in Section 5.

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[15] All bond returns in this study are expressed in terms of the equivalent continuously compounded return to a five percent notional bond. Since we compute the bond price indices using the same convention, the specification of five percent for the notional bond does not affect the results. It only determines the extent to which the price indices trend over time.

[16] The three-factor model allows the data to choose a benchmark index for the bond that reflects its duration and credit quality. Previous research supports the use of separate indexes for interest rate and credit risks in models of bond returns (e.g., Cornell and Green (1991) and Blume, Keim, and Patel (1991)). Hotchkiss and Ronen (2002) also incorporate indexes into return models.

Combining the last three equations produces our version of the Harris and Piwowar transaction cost estimation model:

$$
\begin{aligned}
&r_{ts}^{P} - Days_{ts}\left(5\% - CouponRate\right) = \\
(7)\qquad &c_0\left(Q_t - Q_s\right) + c_1\left(Q_t \frac{1}{S_t} - Q_s \frac{1}{S_s}\right) + c_2\left(Q_t \log S_t - Q_s \log S_s\right) \\
&+ c_3\left(Q_t S_t - Q_s S_s\right) + c_4\left(Q_t S_t^2 - Q_s S_s^2\right) \\
&+ \beta_1 AveIndexRet_{ts} + \beta_2 DurationDif_{ts} + \beta_3 CreditDif_{ts} + \eta_{ts}
\end{aligned}
$$

where the left hand side is simply the continuously compounded bond return expressed as the equivalent rate on a notional five percent coupon bond, and

(8) $$\eta_{ts} = \varepsilon_{ts} + Q_t\kappa_t - Q_s\kappa_s + I_t^D\delta_t - I_s^D\delta_s$$

is the regression error term.[17] The mean of the error term is zero and its variance is given by

(9) $$\sigma_{ts}^2 = N_{ts}^{Sessions}\sigma_{Sessions}^2 + D_{ts}\sigma_{\delta}^2 + \left(2 - D_{ts}\right)\sigma_{\kappa}^2$$

where D_{ts} equals 0, 1 or 2 depending on whether trades t and s represent 0, 1 or 2 interdealer trades. Harris and Piwowar assume that the distributions of κ_t and δ_t have zero means, are serially independent, and independent of everything else, so that the last four terms of (8) are independent of all the right hand side terms in (7) despite the fact that both sets of terms involve the *Q* indicator variables.

We estimate this model using the iterated weighted least squares method described in Harris and Piwowar. Using weights given by the inverse of estimates of σ_{ts}^2 ensures that we give the greatest weights to trade pairs from which we expect to learn the most about transaction costs.

3.2 The Cross-Sectional Methods

Our cross-sectional analyses consider how estimated transaction costs vary across bonds. We analyze both retail and institutional sized trades at various representative dollar sizes.

The estimated quadratic cost function characterizes how costs vary by trade size. For a given trade size *S*, the estimated cost implied by the model is the linear combination of the estimated coefficients.

[17] The Harris and Piwowar model is a restricted version of our model. Their model does not include the last two terms in the cost function or the credit difference in the factor return expression. Also, we employ a three factor interest rate model where they only employ a two factor model.

(10) $\hat{c}(S) = \hat{c}_0 + \hat{c}_1 \frac{1}{S} + \hat{c}_2 \log S + \hat{c}_3 S + \hat{c}_4 S^2$.

The estimated error variance of this estimate is given by

(11) $Var(\hat{c}(S)) = \mathbf{D}\, \hat{\Sigma}_{\hat{c}} \mathbf{D}'$

where $\hat{\Sigma}_{\hat{c}}$ is the estimated variance-covariance matrix of the coefficient estimators and

(12) $\mathbf{D} = \left[1 \quad \frac{1}{S} \quad \log S \quad S \quad S^2 \right]$.

Harris and Piwowar note that the estimated values of the cost function coefficients suffer from a multicollinearity problem since their associated regressors are inversely correlated. Their estimator errors therefore tend to be large and correlated with each other. However, this problem does not affect the linear combination of the coefficients, which is generally well identified for trade sizes that are not far from the data. For trade sizes that are larger than the trades upon which the estimates are based, the cost estimate error variance ultimately increases with S^4. For trade sizes that are smaller than the trades upon which the estimates are based, the cost estimate error variance ultimately increases (as sizes become smaller) with the inverse of S^2.

The cross-sectional analyses reported below use cross-sectional regression models to relate the estimated costs computed from (10) to various bond characteristics. Again following Harris and Piwowar, we estimate these models using weighted least squares where the weights are given by the inverse of the cost estimate error variance in (11). This weighting procedure ensures that our results reflect the information available in the data. In particular, the weighting procedure allows us to include all bonds in our cross-sectional analyses without worrying about whether any particular bond provides useful information about the trade sizes in question. If trading in a bond cannot provide such information, its cost estimate error variance will be very large and the bond will have essentially no effect on the results. This may happen if the time-series regression is over identified by only one observation or if the time-series regression sample has no trades near in size to the trade size being estimated. Our weighting scheme thus allows us to endogenously choose the appropriate cross-sectional sample for our various analyses.[18]

[18] As noted by Harris and Piwowar, the application of this method depends critically on the estimated error variance of the cost estimates. By chance, this variance will be estimated with extreme error when the model is only just

4. Time-Series Results

We estimate the transaction cost estimation model (7) separately for all bonds in our sample. Average customer transaction costs should be positive since customers in dealer markets generally pay the bid/ask spread when trading. Table 4 shows that a majority of the estimates are positive for all trade sizes. The fraction that is negative rises with trade size because large trades are less common than small trades in the sample. The estimates therefore are less accurate at such sizes. The fraction also rises because large trades apparently are less costly than small trades.

Figure 1 plots cross-sectional mean cost estimates across all bonds in the sample, weighted by the inverse of their estimation error variances, for a wide range of trade sizes. Also plotted is the weighted average of the 95 percent confidence intervals associated with each bond cost estimate. As expected, the average confidence interval is widest where the data are sparsest.[19]

The estimated transaction costs decrease with trade size. The average round-trip transaction cost for a representative retail order size of 20,000 dollars is 1.38 percent of price (69bps × 2), while the average round-trip cost for a representative institutional order size of 200,000 dollars is only 0.54 percent (27bps × 2). These results may indicate that institutional traders generally negotiate better prices than do retail traders, or that dealers price their trades to cover fixed trade costs.

While both explanations may be valid, the shape of the average cost function suggests that the former explanation is the more important. The OLS fit of

$$\hat{c} = a_0 + a_1 \frac{1}{S} \qquad (13)$$

to the 11 average cost estimates used to construct the plotted average cost function is extremely poor (not shown). If the decline in costs with increasing size were simply due to spreading a fixed cost (a_1) over greater size, this line would closely fit the plotted average cost function.

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barely identified. To avoid this problem, we use the Bayesian shrinkage estimator introduced in the appendix to Harris and Piwowar to estimate regression mean squared errors.

[19] The confidence intervals are for the point estimates of the cost function at given sizes, and not for the cost function as a whole. Since these confidence intervals depend on the same three estimated coefficients, they are highly correlated.

Although fixed costs probably account for much of the curvature of the average cost function for small trades, they do not explain the reduction of costs over the entire range.

The average cost function could be downward sloped if large traders choose to trade bonds that are more liquid. The downward sloping average thus may be due to selection rather than negotiation skills. To rule out this explanation, for each bond, we compute the derivative of the cost function at various sizes. The last column of Table 4 shows that the average derivative is negative, which suggests that the slope of the average is due to the average derivative and not to sample selection.

The downward sloping cost curve is surprising given the upward sloping costs that generally characterize all but the largest equity trades.[20] We attribute the difference primarily to the lack of trade transparency in the corporate bond market. Larger traders undoubtedly know more about values than do smaller traders because they are more likely to be institutional traders who trade frequently.

Differences in transparency also can explain the differences in average transaction costs between the two markets. Effective spreads in equity markets for retail sized trades average less than 40 basis points in contrast to the 138 basis points that we estimate for corporate bonds of 20,000 dollars.[21] We cannot reasonably attribute this cost difference to adverse selection because equities generally are subject to much more credit risk than are corporate bonds. Dealer inventory considerations probably also cannot explain the differences since the returns to most corporate bonds are highly correlated with each other and with highly liquid cash and derivative treasury instruments so that dealers can hedge their positions. Moreover, dealers can also hedge credit risk using the issuer's equities. The only credible explanation for the cost difference is the different market structures, and the most important difference is transparency.

The results we obtain for 2003 TRACE corporate bond sample are very similar to those obtained in Harris and Piwowar (2004) for the 2000 MRSB municipal bond sample. In both cases, the estimated cost functions decline significantly with size. However, the estimated bond trading costs are about 40 percent lower for the corporate bonds than for the municipal bonds at every size level. The difference may be due to the different time periods or to the fact that

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[20] Large equity block trades are often arranged by traders (or their brokers) who often know that the trade initiator is not well informed. Costs for such trades are generally lower than they would be if the traders were anonymous to each other.

corporate bonds trade in more active and more transparent markets.[22] The difference cannot be due to differences in credit quality since the average municipal bond is much more secure than the average corporate bond.

To determine the extent to which the average cost results depend on the functional form chosen for the cost function, we specified and estimated nine alternative functions. These alternatives include

$$c(S_t) = c_0 + c_1 \frac{1}{S_t} + c_2 \log S_t + c_3 S_t + c_4 S_t^2 + c_5 S_t^3 \tag{14}$$

and various nested models obtained by setting coefficients in (14) to zero. The results reported in this study are based on the five-parameter model obtained by constraining c_5 to zero. Figure 2 plots the nine estimated cost curves. The curves lie very close to each other, which suggests that the average cost results do not depend much on the chosen functional form. We chose our five-parameter model because it produced results most similar to the six-parameter model. Harris and Piwowar use the three-parameter model obtained by setting c_3, c_4, and c_5 to zero to conserve degrees of freedom in their regression model. We chose a larger model because the corporate bonds are more actively traded than the municipal bonds.

The four panels of Figure 3 present mean estimated cost functions (similar to the mean cost function presented in Figure 1) computed separately for each class of our four main classification variables. Panel A plots the mean cost estimates for four transparency classes. The first class includes bonds for which prices were never transparent during 2003 and the last class includes bonds for price prices were always TRACE transparent in 2003. The transparent bonds have lower transaction costs than the opaque bonds, especially for small and large trades. The other two transparency classes include bonds phased-into TRACE during 2003 (or high-yield bonds phased-out) and ABS-listed bonds that were never TRACE transparent in 2003. The bonds that were TRACE transparent for part of 2003 look very much like the fully transparent bonds, probably because most of these bonds were transparent for ten of the twelve sample months. The listed bonds have lower transaction costs than the opaque bonds only in the small

[21] Our transaction cost measures estimate effective half spreads. Thus, a cost of 69 basis points represents an effective spread of 138 basis points.
[22] During 2000, the MRSB disseminated trade prices only on the next day and only for bonds that traded four times or more on that day.

trade sizes. This result is likely due to the general perception that ABS is an odd lot market whose prices are only relevant for small trades.

Results for our four credit quality classes appear in Panel B. Not surprisingly, highly rated bonds are cheaper to trade than low rated bonds. The difference between the superior and other investment grade bonds is negligible, but the difference between these two classes and the speculative grade bonds show that high-yield bonds are almost twice as costly to trade as investment grade bonds. More striking are the huge transaction costs for defaulted bonds. These results suggest that adverse selection widens effective spreads in low quality bonds.

Panel C plots mean cost estimates separately for small, medium and large bonds issues. The smaller bonds have higher transaction costs in all but the smallest trades. The transaction costs for medium bonds are greater than for large bonds for large and small trades, otherwise the costs of trading these two classes of bonds are quite similar.

Panel D presents results for our three trading activity classes. Interestingly, transaction costs only appear to be significantly related to trading activity for the most active (an average of more than 1 trade per day) category. Transaction costs are the highest for this category throughout the entire retail trade size ranges and some of the institutional trade size range. These results are surprising since costs are generally lower in active equity markets than in inactive equity markets.

The results reported in the various panels of Figure 3 are univariate results that do not control for bond characteristics that may be correlated with trading activity, credit quality, issue size, transparency, or for the correlations among these characteristics. The next section describes the regression analyses we use to separately identify the contributions of these (and other) variables to total transaction costs.

5. Cross-sectional Determinants of Transaction Costs

This section presents estimation results for regression models that characterize cross-sectional determinants of transaction costs. The dependent variables are percentage transaction costs estimated for various representative trade sizes.

Two sources of error contribute to the error terms in these models. The first is due to error in the transaction costs estimate. The second is due to variation of the data around the predicted model. We assume that the variance of the former component is proportional to the estimated error variance of the estimate, and we assume that the variance of the latter component is constant. We estimate the resulting local variance components model in stages. We first use WLS to estimate the regression model using weights given by the inverse of the estimated estimate error variances. We then regress the squared residuals on an intercept and the estimated estimator error variances to estimate the constant and variable variance components.[23] Finally, we reestimate the regression model using the inverses of the predicted values from this regression as weights. This weighting scheme ensures that we focus the analysis on those bonds that provide the most information about costs at that size while allowing for typical variation about the regression model.

The regressions are all reduced form models that exclude endogenous variables from the set of explanatory variables. The joint determination of transaction costs and of trading activity causes problems if both are include in the same regression. Demand theory suggests that investors trade more when the cost of trading is low, and supply theory suggests that dealers offer more competitive prices when substantial trading activity attracts many dealers. Transactions costs and trading activity, therefore, are endogenous variables.

Unbiased econometric estimation of a structural model requires a set of instrumental variables that are highly correlated with the dependent variables. Regrettably, our sample does not include much exogenous information that can explain why some bonds trade more often than do other bonds. Without enough such information, simultaneous equations methods become noisy and unreliable. We therefore present only reduced form results.

The first set of results presented in Table 5 concern regressors that represent credit quality. Three dummy variables indicate whether the bond is rated BBB, B or BB, or C and below. The coefficient estimates indicate that transaction costs increase as credit quality decreases. For representative trade size of 20 bonds (20,000 dollars), the effective half spread for BBB bonds is 3.6 basis points more than that of bonds rated A and above. This difference rises to 16 basis points for other investment quality bonds (B and BB) and to 26 basis points for speculative bonds (C and below). These differences are all highly statistically significant and are consistent with the well-known and well-tested adverse selection theory of spreads.

Also included in this set of regressors are other variables that may indirectly indicate credit quality. Transaction costs are higher for bonds with high coupon rates or low prices. The former is probably a good proxy for poor credit quality while the later generally reflects market

[23] The weights in this estimate are the inverses of the squares of the estimated error variances.

perception of credit quality. A dummy that indicates whether the issue is in default is highly significant when the average price variable does not appear in the regression (results not presented). It is only significantly positive for the estimated transaction costs for large representative transaction sizes in these regressions. Finally, transaction costs are significantly higher for convertible bonds than for straight bonds. Convertible bonds are often riskier than other bonds because they embody credit risk of the underlying stocks.

The positive and highly significant coefficients on time since issuance indicate that newer bonds are less expensive to trade than well-seasoned bonds. This result is consistent with well-known characteristics in the government bond markets in which the costs of trading bonds-on-the-run trade are lower than the costs of trading seasoned issues.[24]

The positive and highly significant coefficients on time to maturity indicate that bonds that mature soon are cheaper to trade than bonds that mature in the distant future. The negative and highly significant coefficients on dummy variables that represent bond features that decrease the expected time to maturity—soon to be called and sinking funds—corroborate these results.[25] The greater uncertainties associated with valuing long-term bonds as compared to short-term bonds probably make the long-term bonds more expensive to trade.[26]

The regression includes inverse price as a regressor to determine whether corporate bond transaction costs have a fixed cost component. The estimated coefficient is only positive and significant in the large representative trade size regressions. This regressor, of course, is highly inversely correlated with the average price regressor. The omission of the latter from the regression makes the inverse price coefficient positive and highly significant for all trade sizes (results not reported). It is thus impossible to confidently identify a fixed cost component if average price is indeed a good proxy for credit quality. Although the results must be interpreted with caution, the fact that the average price regressor largely knocks out the inverse price regressor suggests that price probably conveys more information about credit quality than about fixed costs.

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[24] See, for example, Sarig and Warga (1989) and Warga (1992).

[25] The TRACE data identify a callable bond as soon to be called if the NASD expects that it will be called soon.

[26] The bond age and time to maturity variables are transformed by the square root function to shrink large values since we do not expect that a one year difference in these variables has more effect when the values are low than high. We did not use the log transformation for this purpose because it expands low values too much.

Large issues have significantly lower transaction costs than do small issues. Although we expected this result, we note that the effect is not overwhelmingly significant. The weak result probably is due to the fact that many large bond issues do not trade often.

The total size of other issues outstanding from the same issuer is a significant positive determinant of transaction cost. This result surprised us because we expected that liquidity in a given issue would benefit from liquidity in other issues. The result may be due to credit problems associated with large levered firms.

Bonds with attached calls and with attached puts had significantly lower estimated transaction costs than those without such features. We found these results surprising since these features complicate bond valuation. The call results may be explained by the fact that investors in 2003 undoubtedly expected that many callable bonds would soon be called since yields by then had dropped significantly since these bonds were issued with high coupons. The bonds thus would behave more like short term bonds than long term bonds, as so have lower transaction costs. Indeed, the results reported above for the bonds identified in TRACE as soon to be called are consistent with this explanation. The bonds most likely to be called are high coupon bonds. Accordingly, when the product of coupon rate times the call dummy is included in the regression, the coefficient on the product is significantly negative and the dummy takes a significantly positive coefficient for all but the large trade sizes (results not reported).[27] The put results may also reflect the fact that the bonds with puts attached will likely be put in the near future, and so may be valued more like short term bonds than long term bonds.

Floating rate bonds are less expensive to trade than standard bonds. These bonds generally have less variable prices than standard bonds because the variation in their coupons generally is correlated with variation in bond yields. They therefore should be somewhat easier to price.

Variable rate bonds have coupons that vary according to some schedule. They are slightly more expensive to trade, probably because of the additional difficulties associated with pricing them.

Four additional variables that represent bond complexity features—noncash call, nonstandard accrual, nonstandard payment and extended or extendable maturity date—all are generally associated with higher bond transaction costs. These features make bonds more difficult to price and thereby may increase transaction costs. Except for the noncash calls, these results are all generally statistically significant.

The next regressors characterize the type of bond and the type of issuer. The results indicate that transaction costs are lower for bonds issued by private issuers (those without publicly traded equity), Rule 144a issues, foreign bonds, global bonds, and bonds issued by utilities.[28] Bonds issued by financial companies are slightly more expensive to trade. The private issuer results for small trade sizes are somewhat surprising since the values of these bonds presumably are harder to determine. However, Alexander, Edwards, and Ferri (2000) show that the bonds of private issuers trade more frequently than similar bonds from public issuers and, thus, may be more liquid. The 144a estimate coefficients are very large and highly significant. Because only large institutions that are Qualified Institutional Buyers (QIBs) can trade 144a bonds, this result is consistent with the ability of large institutions to negotiate better prices than can other investors.

The final two regressors characterize whether bond prices were transparent in TRACE or in the NYSE ABS trading system. The estimated coefficients for both variables are significantly negative, which indicates that transparency is associated with lower transaction costs. The ABS results are stronger than the TRACE results, probably because ABS prices are immediately transparent, because ABS quotes are transparent, and because traders may be more used to looking to ABS than to TRACE for price information. We expect that the TRACE effect would increase substantially if TRACE data were available more quickly and if it were available for more bonds. Not surprisingly, the ABS results are also stronger for small trades, which may be related to the use of ABS for small trades.

Almost all of the quantitative results obtained from these regressions are larger in absolute value for smaller transaction sizes than for larger sizes. These results suggest that institutional traders are able to negotiate better prices for bonds of all types than can retail traders.

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[27] We did not include this product in the reported regressions because we felt that a proper analysis of this problem would require a full model of the probability that bonds would be called. We attempted to construct such a model, but found that our efforts were severely limited by the data available to us in the TRACE dataset.

[28] "Rule 144a" refers to the rule titled "Rule 144a – Private Resales of Securities to Institutions" promulgated under the Securities Act of 1993, which allows qualified institutional buyers to buy and trade unregistered securities.

Overall, the cross-sectional transaction cost results suggest that corporate bond transaction costs are negatively related to credit rating and often positively related to instrument complexity. Younger bonds and bonds with a shorter time-to-expected-maturity are cheaper to trade than older bonds and bonds with a longer time-to-expected-maturity. These results are similar to those reported in Harris and Piwowar (2004), although Harris and Piwowar found stronger results for the complexity measures.

The above analyses show that transparent bonds had lower transaction costs in the 2003 period than did nontransparent bonds, after controlling for many other factors that affect transaction costs. Although our controls for other factors are quite comprehensive, it is always possible some omitted variable or some nonlinearity in the population distribution may account for the results.[29] In which case, the residuals of the cross-sectional regression would be correlated so that the significance of our results would be overstated. We address these potential problems in the next section by analyzing how liquidity varies though time for bonds that were made TRACE-transparent during our 2003 sample period.

6. Time Varying Liquidity

This section describes how we estimate and analyze time varying liquidity. The previously described analyses use separate time series regressions to estimate average transaction costs for each bond, which we then analyze using cross-sectional regressions. In this section, we introduce a pooled time series regression model that we use to estimate average transaction costs for each day for a class of bonds. We estimate the daily average transaction costs for bonds that were made transparent during 2003, and compare these estimates to those for comparable bonds that were either TRACE-transparent throughout 2003 or never TRACE-transparent in 2003.

The regression model that we use to estimate daily transaction costs differs only in two respects from the time series regression model that we used to estimate average transaction costs for a given bond. First, we specify separate average transaction cost functions, $c_T\left(S_t\right)$, for each day T in the sample. (The functional form, however, is the same for each day.) Second, to minimize the total number of parameters to be estimated, we use the following three-parameter average cost function:[30]

[29] In either case, the problem would have to be correlated with our transparency indicator.
[30] We also used the five-parameter specification used above and obtained similar, though understandably less powerful results.

(15) $$c_T\left(S_t\right) = c_{0T} + c_{1T}\frac{1}{S_t} + c_{2T}\log S_t + \kappa_t \,.$$

Second, we model the change in value between bond trades (for a given bond) as

(16) $$\log V_t - \log V_s = f_s r_S + \sum_{J=S+1}^{T-1} r_J + f_t r_T + e_{st}$$

where *S* is the day on which trade *s* took place and *T* is the day on which a subsequent trade *t* took place, r_J is the common index return (to be estimated) for day *J* and f_s and f_t, respectively, are the fractions of the *S* and *T* trading days overlapped by the period spanned by transactions *s* and *t*. This portion of the specification is the same as appears in many paired trade regression index estimation procedures. With these changes, the regression model is

(17) $$\begin{aligned} & r_{ts}^P - Days_{ts}\left(5\% - CouponRate\right) = \\ & \quad c_{0T}Q_t - c_{0S}Q_s + c_{1T}Q_t\frac{1}{S_t} - c_{1S}Q_s\frac{1}{S_s} + c_{2T}Q_t\log S_t - c_{2S}Q_s\log S_s \\ & \quad + f_s r_S + \sum_{J=S+1}^{T-1} r_J + f_t r_T + \eta_{ts} \end{aligned}$$

with the variance of η_{ts} given as before by (9) above. As before, we estimate the model in stages using weighted least squares where the weights are equal to the predicted values of the regression of the squared residuals on the independent variables appearing in the residual variation expression.

This model has four regression coefficients for each of the 252 days in the sample, for a total of 1,008 parameters. To reduce the total estimation time, we estimate the model using a three-month wide sliding window that we move forward one month at a time. We assemble our time series of coefficient estimates from the center months of each of the sliding regressions. For January and December, we respectively use estimates from the first and last regressions.

We compute transaction costs for various representative transaction sizes by evaluating the estimated transaction cost functions at the representative transaction sizes. Using the estimated variance-covariance matrix of the estimators, we also compute daily standard errors of the various daily transaction cost estimates.

We initially estimate the model for all bonds that the NASD made TRACE-transparent on March 1, 2003. These include all bonds rated A and above with original issues sizes greater than 100 million dollars and less than one million dollars. This sample (T) includes 952,137 trades in 3,004 bonds.

We then estimate the model for three comparison samples. The first comparison sample (C1) includes all bonds rated A and above that were TRACE-transparent throughout 2003. The NASD made these bonds transparent on July 1, 2002 because their original issue sizes are greater than one billion dollars. This sample includes 1,516,022 trades in 814 bonds. The second sample (C2) includes all bonds rated A and above that were never TRACE-transparent during 2003.[31] The original issue sizes of these bonds were all less than 100 million dollars. This sample includes 1,014,380 trades in 8,952 bonds. The third comparison sample (C3) includes all BBB bonds with original issue sizes between 100 million and one billion dollars that were never TRACE-transparent during 2003. This sample includes 1,219,292 trades in 4,065 bonds. The first two comparison samples consist of bonds with comparable ratings but different issue sizes whereas the last sample consists of slightly lower grade investment quality bonds of similar size.

We identify the effect of transparency on the bonds that became TRACE-transparent by comparing daily estimates of their transaction costs with those for the three comparison samples. The comparison samples thus allow us to control for any time varying changes in liquidity that might be unrelated to the transparency event. In particular, we compute the daily time series of differences between average transaction cost estimates for the March 1 bonds and those of each comparison group. We then separately regress these differences on a dummy variable that indicates with a value of one dates (after February 28) on which prices were TRACE-transparent. The estimated dummy variable coefficient is a difference of differences. The standard error of this estimate reflects the time series variation in the differences.

Since the dependent variable is estimated with noise, the residual error of the regression includes a component that reflects the noise in the dependent variable in addition to a component that reflects the time series variation in the costs about their mean. We estimate the variance of the former component from the estimated variance of the cost estimates,[32] and assume that the

[31] We identify a bond as rated A and above if Moody's or S&P rated it A or above any time in 2003.

[32] In particular, we sum the estimated variances for the two cost estimates that appear in the difference between cost estimates. The variance of the difference also includes a covariance term that we crudely estimate by correlating the daily cost estimate variances. The results are largely affected by whether we adjust for this covariance or not. The invariance is due to the fact that the estimator error for the April 14 sample is much larger than that of either of the other two samples because the number of trades in the April 14 sample is a small fraction of the numbers in the other samples.

variance of the latter component is constant. We estimate the resulting model using maximum likelihood methods.

The results in Table 6 confirm that transparency significantly decreased transaction costs for the bonds that were made transparent on March 1. Transaction costs decreased in comparison to each of the three comparison samples. The decrease in transaction costs was generally greater for smaller trade sizes, most probably because larger traders already had substantial knowledge of bond values, and hence lower initial transaction costs.

The decrease was greater when measured relative to the bonds that never were made transparent (C2 and C3) than relative to the bonds that were already transparent (C1). The relation between the C1 and C2 results is mechanically due to the fact that transaction costs for the already transparent bonds (C1) fell relative those of the never transparent bonds (C2). This decrease may be due to traders becoming more aware of the transparent prices, or perhaps to cross-sectional differences in time varying liquidity that were correlated with original issue size. However, note that little average difference exists between the two controls samples (C2 and C3) for which prices were never transparent despite their cross-sectional differences: C2 consists of small bond issues rated A and above while C3 consists of intermediate size BBB issues.

The NASD made 120 intermediate sized BBB rated bonds transparent on April 14. Using the methods described above, we compared estimated transaction costs in these bonds to those estimated for comparison samples of all BBB rated bonds that were continuously transparent and that were never transparent in 2003. The results in Table 7 show that although the magnitudes of the changes are smaller than those in Table 6, these results are still statistically and economically significant. The effect of transparency on the transaction costs in these BBB bonds may have been less than on the intermediate sized A and above bonds because traders may not have known to look for their prices.

7. Conclusion

Corporations raise very substantial financing in the bond markets. A better understanding of the liquidity of these markets thus may help corporations identify ways to lower their costs of capital. We examine secondary trading costs in the corporate bond market using improved methods and more comprehensive data than earlier studies. We find that bond price transparency lowers transaction costs. Accordingly, additional bond transparency may lower corporate costs of capital.

Our results show that corporate bonds are expensive for retail investors to trade. Effective spreads in corporate bonds average 1.4 percent of price for representative retail-sized trades (20,000 dollars). This is the equivalent of almost three months of total annual return for a bond with a 6 percent yield-to-maturity, or 56 cents per share for a 40-dollar stock. If transaction costs are a deterrent to retail interest, we would expect retail interest to increase with the lower transaction costs associated with transparency.

Unlike in the equity markets, bond transaction costs are much lower for institutional size transactions. Large traders undoubtedly negotiate better prices because they are better informed about values than are small investors who rarely trade and who typically lack the analytic capacity to estimate fundamental bond values. Increased transparency thus would especially benefit retail investors.

The publication of trade prices for TRACE-transparent bonds occurs as late as 45 minutes after the trade. The effects of transparency on bond transaction costs that we measure probably thus underestimate the benefits that immediate transparency might produce.

The strongest arguments against transparency involve concerns about how exposure would make it more difficult for dealers to manage inventory, especially in bonds with poor credit. The management of inventory problems, however, is easier in the debt markets than in the equity markets because credit risk is smaller in the former than the latter and because credit risk can be hedged in the equity markets. Accordingly, given the great liquidity observed in fully transparent equity markets, and our empirical results, we believe that it would be extremely unlikely that increased bond market transparency would increase bond transaction costs.

Rather, additional transparency will very likely permit the creation of new market structures and innovative dealing strategies that will further reduce transaction costs. If so, the benefits of additional transparency estimated in this paper are far smaller than will likely be obtained if the corporate bond markets were made more transparent.

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Table 1: Sample Composition

This table describes the effects of the various filters used to construct the TRACE bond sample analyzed in this study. The data are drawn from the complete 2003 TRACE transaction dataset and from five snapshots of the TRACE master file supplied by the NASD. Securities that did not trade are the issues that appear in the master files but not in the transaction file. TRACE classifies the majority of these bonds as inactive bonds that are not available for trading. We delete any trades that were corrected or duplicate ("corrected trades"), trades with a recorded size that is not an integer, with an execution date prior to the TRACE "First Active Date", with an execution date after the maturity date or with a recorded size greater than half of the total issue size ("suspect trades"). We classify trades as having suspect prices if they failed to pass filters designed to identify likely data entry errors while allowing for reasonable price changes. Since TRACE requires dealers to report interdealer trades, we delete duplicate records of interdealer trades. Bonds with missing duration information do not have maturity date, coupon rate, or coupon payment frequency information in the TRACE master files. Finally, we remove from the sample those bonds that did not have enough observations to identify the transaction cost regression model that we used to estimate the bond transaction costs.

	Bonds	Trades	Dollar volume (billions)
Entire TRACE database	68,877	8,668,987	9,413
Less securities that did not trade	46,432	0	0
Less trades with no master matches	14	148	0
Subtotal of securities that traded	22,453	8,668,839	9,412
Less preferred stocks and inactive bonds	59	1,622	2
Subtotal of active bonds	22,394	8,667,217	9,410
Less corrected trades	17,689	718,440	3,073
Subtotal without corrected trades	22,262	7,948,777	6,338
Less suspect trades	3,062	58,605	67
Less suspected pricing data errors	7,215	38,009	22
Subtotal after filtering trades	21,708	7,852,163	5,879
Less duplicate interdealer trades	16,295	1,169,662	718
Less bonds with missing duration information	46	5,036	26
Subtotal after removing duplicate trades	21,662	6,677,465	5,135
Less bonds with unidentified cost regressions	4,916	27,707	56
Final sample	16,746	6,649,758	5,079

Table 2: Sample Characteristics

This table summarizes the cross-sectional distributions of volumes and trade sizes for the sample of bonds analyzed in this study. The TRACE sample consists of 6.6 million trades in almost 16,746 corporate bonds. Unless otherwise noted, the statistics summarize means computed for each bond. Retail- and institutional-size trades are respectively identified as those smaller and larger than 100 bonds.

Trading characteristic	Mean	1st percentile	Median	99th percentile
Mean number of trades per day	1.9	<0.1	0.6	21.9
Interdealer	0.6	0.0	<0.1	7.5
Retail size customer	0.9	0.0	0.2	10.2
Institutional size customer	0.5	0.0	<0.1	5.2
Buy customer volume	0.8	<0.1	0.2	9.3
Sell customer volume	0.5	<0.1	0.2	6.0
Mean dollar volume ($ thousand)	161.9	<0.1	20.6	2,027.4
Interdealer	40.1	0.0	2.7	636.4
Retail size customer	1.8	0.0	0.4	22.8
Institutional size customer	120.0	0.0	14.9	1,455.9
Buy customer volume	62.7	<0.1	8.3	743.0
Sell customer volume	59.1	<0.1	7.5	714.4
Mean annualized turnover (percent)	83.0	0.5	51.7	468.5
Interdealer	21.1	0.0	9.8	143.8
Retail size customer	6.0	0.0	1.2	40.7
Institutional size customer	56.0	0.0	26.8	351.3
Frequency of days with a trade (percent)	33.2	2.4	23.4	99.6
Interdealer	21.0	0.0	8.3	99.6
Retail size customer	25.3	0.0	13.6	99.6
Institutional size customer	22.1	0.0	8.1	99.6
Trade size in value ($ thousand)	1,154.6	10.1	351.9	12,279.3
Minimum	31.2	0.4	2.0	545.0
Mode	546.2	1.0	11.5	9,806.8
Median	583.5	5.4	29.7	6,806.3
Maximum	12,401.1	25.9	5,091.1	105,242.9
Interdealer	824.1	7.7	192.0	8,440.9
Retail size customer	24.6	4.5	21.5	72.3
Institutional size customer	1,935.4	98.0	1,264.6	15,461.2
Customer buys	1,239.5	8.1	370.0	13,421.6
Customer sells	1,294.0	9.2	425.9	13,005.3
Simple statistics across trades	763.8	1.1	31.2	10,397.0
Mean number of dealers	35.6	2.0	22.0	199.0
Interdealer	17.9	1.0	11.0	110.0
Retail size	12.9	1.0	8.0	74.0
Institutional size	8.7	1.0	6.0	37.0

Table 3: Cross-sectional Bond Characteristics

This table characterizes the cross-sectional distributions of various bond features in the TRACE data. A bond is classified as transparent if it is transparent at any point in 2003. Credit quality is based on the average credit quality during 2003. A bond is classified as defaulted if it was in default at any point in 2003. The bonds are classified into age categories based on their average age in 2003. S&P assigns the industrial classification of a bond with respect to the nature of the bond and not that of the issuer. Equity status refers to whether the bonds issuer has publicly traded equity in the US. Subsidiaries have the same equity status as their parent.

	Bonds in sample		Trades in sample		Total value traded	
Feature	Number	Percent	Thousands	Percent	$ Billions	Percent
Bond transparency						
TRACE-disseminated	3,719	22.2	3,279	49.3	2,712	53.4
ABS-listed	444	2.7	306	4.6	171	3.4
Both ABS and TRACE	185	1.1	157	2.4	112	2.2
Not transparent	12,768	76.2	3,222	48.4	2,308	45.4
Credit quality						
Superior (AA and up)	1,559	9.3	496	7.5	412	8.1
Other investment grade (BBB-A)	10,520	62.8	4,164	62.6	2,906	57.2
Speculative (below BBB)	3,891	23.2	1,752	26.4	1,575	31.0
Not Rated	428	2.6	81	1.2	97	1.9
Defaulted	490	2.9	157	2.4	89	1.8
Issue size						
Small (< $100 million)	6,728	40.2	854	12.8	65	1.3
Medium ($100 - $500 million)	7,801	46.6	2,257	33.9	1,633	32.2
Large (> $500 million)	2,268	13.5	3,539	53.2	3,380	66.6
Age						
0-3 months	3,334	19.9	696	10.5	804	15.8
3-6 months	1,115	6.7	478	7.2	620	12.2
6 months- 1 year	1,350	8.1	532	8.0	449	8.9
1 year – ½ life	6,222	37.2	3,393	51.0	2,404	47.3
½ life – maturity	4,725	28.2	1,551	23.3	801	15.8
Industry						
Finance	8,230	49.1	3,028	45.5	1,915	37.7
Utilities	6,254	37.3	3,001	45.1	2,594	51.1
Other	2,298	13.7	621	9.3	569	11.2
Equity status						
Publicly Traded in US	15,307	91.4	6,308	94.9	4,721	92.9
Private or Foreign	1,439	8.6	342	5.1	358	7.1
Bond complexity features						
Callable	5,710	34.1	1,693	25.7	1,173	23.0
Non-cash Call	567	3.4	118	1.8	89	1.8
Putable	736	4.4	248	3.7	442	8.7
Sinking Fund	342	2.0	28	0.4	38	0.8
Convertible	896	5.4	4,549	6.8	635	12.5
Extendible	16	0.1	2	<0.1	6	0.1
Paid in Kind	12	0.1	1	<0.1	1	<0.1
Floating Rate Coupon	704	4.2	61	0.9	310	6.1
Variable Rate Coupon	340	2.0	101	1.5	123	2.4
Combination of floating/fixed	30	0.2	5	<0.1	13	0.3
Nonstandard payment frequency	3,586	21.4	648	9.7	532	10.5
Nonstandard accrual frequency	852	5.1	260	3.9	444	8.7
Type of issue						
Global	2,493	14.9	2,735	41.1	2,303	45.3
Euro	3	<0.1	<0.1	<0.1	<0.1	<0.1
Foreign	833	5.0	198	3.0	285	5.6
Rule 144a issue	1,521	9.1	271	4.1	672	13.2
Asset status						
Soon to be called	571	3.4	27	0.4	15	0.3
Reopened	232	1.4	603	9.1	453	8.9
Defeased	3	<0.1	0.3	<0.1	<0.1	<0.1

Table 4: Cross-sectional Characterizations of the Estimated Cost Functions

This table presents cross-sectional statistics that characterize average trade costs for various trade sizes implied by the estimated coefficients of the transaction cost estimation model:

$$
\begin{aligned}
& r_{ts}^{P} - Days_{ts}\left(5\% - CouponRate\right) = \\
& \quad c_0\left(Q_t - Q_s\right) + c_1\left(Q_t \frac{1}{S_t} - Q_s \frac{1}{S_s}\right) + c_2\left(Q_t \log S_t - Q_s \log S_s\right) \\
& \quad + c_3\left(Q_t S_t - Q_s S_s\right) + c_4\left(Q_t S_t^2 - Q_s S_s^2\right) \\
& \quad + \beta_1 AveIndexRet_{ts} + \beta_2 DurationDif_{ts} + \beta_3 CreditDif_{ts} + \eta_{ts}
\end{aligned}
$$

The dependent variable is the continuously compounded return—expressed as the equivalent return to a notional five percent bond—between trades. Days counts the number of calendar days between trades and CouponRate is the bond coupon rate. $AveIndexRet_{ts}$ is the index return for the average bond between trades t and s and $DurationDif_{ts}$ and $CreditDif_{ts}$ are the corresponding differences between index returns for long and short term bonds and high and low quality bonds. The cost estimates—which are effective half-spreads—are obtained from time-series regressions estimated separated for each of the 16,746 bonds in the sample. The estimated costs for a trade of size S are computed from $\hat{c}(S) = \hat{c}_0 + \hat{c}_1 \frac{1}{S} + \hat{c}_2 \log S + \hat{c}_3 S + \hat{c}_4 S^2$. The slope of the average cost function at trade size S is computed as $\hat{c}'(S) = -\hat{c}_1 \frac{1}{S^2} + \hat{c}_2 \frac{1}{S} + \hat{c}_3 + 2\hat{c}_4 S$. The weights used to compute the weighted means are the inverses of the estimated estimator variances of the respective cost and slope estimates.

Trade size ($1,000)	Weighted mean cost (basis points)	Median cost (basis points)	Fraction positive (percent)	Weighted mean slope of the cost function (basis points per $1,000)
5	83	70	86.4	-0.01
10	79	66	89.8	-0.82
20	69	57	90.8	-0.63
50	51	39	89.4	-0.30
100	38	27	86.2	-0.07
200	27	19	81.2	-0.07
500	16	12	75.9	-0.02
1,000	11	8	72.2	-0.01
2,000	7	5	68.2	-0.003
5,000	4	2	65.4	>0.001
10,000	5	2	60.9	0.002

Table 5: Cross-sectional Transaction Cost Determinants

This table reports estimated regression coefficients in which estimated percentage transaction costs for various representative trade sizes are related to various bond characteristics. The transaction cost estimates are obtained for each bond by estimating (7) as described in the text. Variables with unit descriptions are continuous and those without are indicators. The regression is estimated using weighted least squares where the weights are the inverses of the predicted values from the regression of the squared OLS residuals on a constant and the estimated error variances of the transaction cost estimates. Coefficient estimate t-statistics appear in parenthesis.

	Coefficient estimate					*t*-statistic				
Representative trade size	10	20	100	200	1000	10	20	100	200	1000
Intercept (basis points)	294	273	169	108	20	37.0	38.6	36.5	29.1	8.0
Credit rating is BBB	4.4	3.6	4.4	5.1	3.6	5.6	4.9	7.0	9.2	8.6
Credit rating is B or BB	19.6	15.7	6.1	6.3	3.1	15.0	11.4	6.6	8.0	5.4
Credit rating is C and below	38.0	26.0	9.9	9.9	5.3	15.6	11.9	6.8	8.6	6.9
Coupon rate	6.3	5.6	3.1	2.1	1.2	24.2	23.5	17.2	14.1	12.6
Average price (percent of par)	-3.1	-2.9	-1.9	-1.3	-0.3	-50.4	-52.6	-50.9	-43.3	-17.8
Bond is in default	-8.9	-5.5	7.8	9.1	8.9	-1.6	-1.1	2.3	3.4	5.3
Bond is convertible to stock	48.5	42.7	29.5	21.7	3.4	20.7	20.0	19.8	18.3	4.4
Years since issuance (sq. root)	7.5	7.6	5.3	4.5	3.2	18.7	20.2	16.7	16.2	15.0
Years to maturity (sq. root)	29.4	26.9	16.2	11.1	3.0	100.5	99.7	76.2	60.7	21.7
Bond is soon to be called	-74.0	-70.6	-40.2	-28.2	-18.7	-18.5	-17.2	-9.7	-7.6	-6.7
Bond has a sinking fund	-40.8	-37.0	-12.8	-2.6	10.8	-6.6	6.6	-3.1	-0.9	6.0
Inverse average price (inverse percent of par)	-1,372.7	-1,098.0	86.2	631.1	1,024.8	-5.8	-5.3	0.7	6.2	13.9
Issue size (sq. root of millions)	-0.06	-0.13	-0.16	-0.16	-0.21	-1.4	-3.5	-5.7	-7.0	-12.5
Total other issues by same issuer (sq. root of millions)	0.05	0.06	0.07	0.06	0.01	13.3	16.0	22.2	21.2	4.7
Attached call	-28.4	-22.3	-11.0	-7.7	0.8	-30.1	-25.2	-14.9	-12.3	1.8
Attached put	-61.1	-59.3	-44.1	-31.9	-7.7	-23.7	-25.7	-28.6	-26.0	-9.6
Floating rate bond	-15.3	-16.3	-11.9	-9.9	-0.5	-5.5	-6.6	-6.5	-6.3	-0.4
Variable rate bond	11.2	9.4	6.1	4.5	2.8	4.2	3.9	3.5	3.1	2.9
Noncash call	0.5	1.0	-0.5	-0.7	0.3	0.2	0.5	-0.3	-0.5	0.3
Nonstandard accrual	7.0	7.8	7.0	5.6	2.6	4.8	5.8	6.8	6.2	3.9
Nonstandard payment	2.6	3.0	0.9	1.3	0.9	2.8	3.3	0.9	1.3	1.0
Maturity date extended or extendable	6.3	6.2	5.2	4.5	2.9	3.6	3.9	4.7	4.8	4.5
Issuer’s equity is private	-13.6	-14.4	-8.2	-3.5	2.2	-7.0	-8.7	-8.4	-4.7	4.6
Rule 144a bond	-59.3	-51.6	-27.2	-17.2	-2.7	-24.3	-27.0	-27.2	-23.4	-6.0
Foreign bond	-3.5	-2.2	-1.9	-2.0	-1.1	-1.8	-1.3	-1.7	-2.3	-1.9
Global bond	-5.8	-5.4	-3.6	-2.1	0.5	-6.3	-6.5	-6.2	-4.3	1.4
Issuer is in finance industry	3.1	3.0	1.7	1.2	1.2	3.9	4.1	3.0	2.5	3.3
Issuer is a utility	-2.4	-2.4	-3.3	-3.3	-2.4	-2.3	-2.4	-4.4	-5.5	-5.7
TRACE-transparent (fraction of trades reported to public)	-0.9	-2.9	-3.8	-2.8	-2.1	-0.8	-2.8	-4.8	-4.2	-4.2
Issue listed on NYSE ABS	-16.8	-12.75	-3.5	-1.8	-0.9	-11.9	-10.0	-3.4	-2.0	-1.3

Table 6: Time Varying Transaction Costs: March 1 Dissemination Date

Mean daily estimated transaction costs in 2003 by representative trade size (in basis points) before and after March 1 for bonds rated A and above that were made TRACE-transparent on March 1 and for three comparison samples of bonds. The first comparison sample consists of all bonds that were TRACE-transparent throughout 2003. The original issue sizes of these bonds are all greater than one billion dollars. The second sample includes all bonds rated A and above that were never TRACE-transparent during 2003. The original issue sizes of these bonds were all less than 100 million dollars. The third comparison sample consists of all BBB bonds with original issue sizes between 100 million and one billion dollars that were never TRACE-transparent during 2003. The daily transaction cost estimates are obtained using the time varying cost regression model described in the text. The means are computed by weighting daily cost estimates by inverse of the estimated variance of the error of the cost estimate. The various differences of differences are computed by subtracting daily cost estimates for one sample from those of another sample, and then regressing the differences on a dummy that takes a value of one for dates after February 28. The regression is weighted by a linear combination of a constant variance and the estimated error variance of the dependent variable, and is estimated using maximum likelihood. The sample consists of 252 trading days in 2003. The daily transaction cost estimates for the four samples are respectively obtained from 952,137, 1,516,022, 1,014,380, and 1,219,292 trades in 3,004, 814, 8,952, and 4,065 bonds. ***, **, * indicate that the transaction costs after March 1 are statistically different at the 1, 5, and 10% levels than the transaction costs before March 1.

		Trade size					
Sample	March 1	5	10	20	100	200	1000
Mean estimates (Basis points)							
T: Bonds rated A & above,	Before	87.2	81.2	73.4	52.2	42.6	20.1
made transparent March 1	After	87.2	78.7**	69.7***	47.9***	38.4***	16.3***
($100M to 1B original issue size)							
C1: Bonds rated A & above,	Before	59.2	55.5	49.8	33.7	26.3	8.8
transparent throughout 2003	After	69.3***	64.9***	58.3***	39.3***	30.6***	10.0*
($1B+ original issue size)							
C2: Bonds rated A & above,	Before	83.7	77.4	70.1	51.6	43.5	24.3
never transparent in 2003	After	95.8***	88.9***	80.4***	58.4***	48.5***	25.4
(<$100M original issue size)							
C3: Bonds rated BBB,	Before	70.7	67.0	61.4	45.5	38.1	20.8
never transparent in 2003	After	89.7***	84.8***	77.2***	55.4***	45.4***	21.7
($100M to 1B original issue size)							
Differences of differences							
T minus C1		-8.9	-12.0	-12.1	-9.8	-8.4	-4.8
		(-6.4)	(-10.0)	(-9.9)	(-9.4)	(-8.7)	(-5.3)
T minus C2		-12.1	-14.0	-13.9	-11.0	-9.2	-4.5
		(-6.2)	(-10.6)	(-10.2)	(-9.3)	(-8.6)	(-4.2)
T minus C3		-19.0	-20.3	-19.4	-14.2	-11.4	-4.6
		(-7.8)	(-13.2)	(-12.8)	(-11.7)	(-10.5)	(-4.2)
C1 minus C2		-2.0	-2.1	-1.8	-1.2	-0.8	0.1
		(-1.8)	(-2.0)	(-2.0)	(-1.5)	(-1.1)	(0.1)
C2 minus C3		-7.0	-6.3	-5.5	-3.2	-2.2	0.2
		(-4.9)	(-5.6)	(-5.4)	(-3.9)	(-2.8)	(0.2)

Table 7: Time Varying Transaction Costs: April 14 Dissemination Date

Mean daily estimated transaction costs in 2003 by representative trade size (in basis points) before and after April 14 for bonds rated BBB that were made TRACE-transparent on April 14 and for two comparison samples of bonds. The first comparison sample consists of all BBB bonds that were TRACE-transparent throughout 2003. The original issue sizes of these bonds are all greater than one billion dollars. The second sample includes all bonds rated BBB that were never TRACE-transparent during 2003. The original issue sizes of these bonds were all less than 1 billion dollars. The daily transaction cost estimates are obtained using the time varying cost regression model described in the text. The means are computed by weighting daily cost estimates by inverse of the estimated variance of the error of the cost estimate. The various differences of differences are computed by subtracting daily cost estimates for one sample from those of another sample, and then regressing the differences on a dummy that takes a value of one for dates after April 13. The regression is weighted by a linear combination of a constant variance and the estimated error variance of the dependent variable, and is estimated using maximum likelihood. The sample consists of 252 trading days in 2003. The daily transaction cost estimates for the three samples are respectively obtained from 59,205, 958,460, and 1,563,140 trades in 120, 198, and 6,281 bonds. . ***, **, * indicate that the transaction costs after April 14 are statistically different at the 1, 5, and 10% levels than the transaction costs before April 14.

		Trade size					
Sample	April 14	5	10	20	100	200	1000
Mean estimates (Basis points)							
T: Bonds rated BBB,	Before	89.8	82.6	74.0	52.0	42.0	19.2
made transparent April 14	After	87.8	79.7**	70.8***	49.1***	39.5***	17.2*
(<$1B original issue size)							
C1: Bonds rated BBB,	Before	61.0	57.1	51.0	33.7	25.7	6.8
transparent throughout 2003	After	65.2***	60.9***	54.4***	35.9***	27.3***	7.1
($1B+ original issue size)							
C2: Bonds rated BBB,	Before	87.1	81.3	73.9	54.5	45.8	25.3
never transparent in 2003	After	95.2***	88.5***	80.1***	58.2***	48.4***	25.3
(<$1B original issue size)							
Differences of differences							
T minus C1		-5.3	-6.8	-6.6	-5.2	-4.4	-2.6
		(-3.5)	(-5.5)	(-5.5)	(-5.0)	(-4.6)	(-2.8)
T minus C2		-8.5	-10.0	-9.3	-6.7	-5.3	-1.9
		(-5.5)	(-8.3)	(-7.2)	(-5.8)	(-5.0)	(-1.8)
C1 minus C2		-3.9	-3.4	-2.8	-1.5	-0.9	0.4
		(-3.7)	(-3.6)	(-3.2)	(-2.1)	(-1.4)	(0.5)

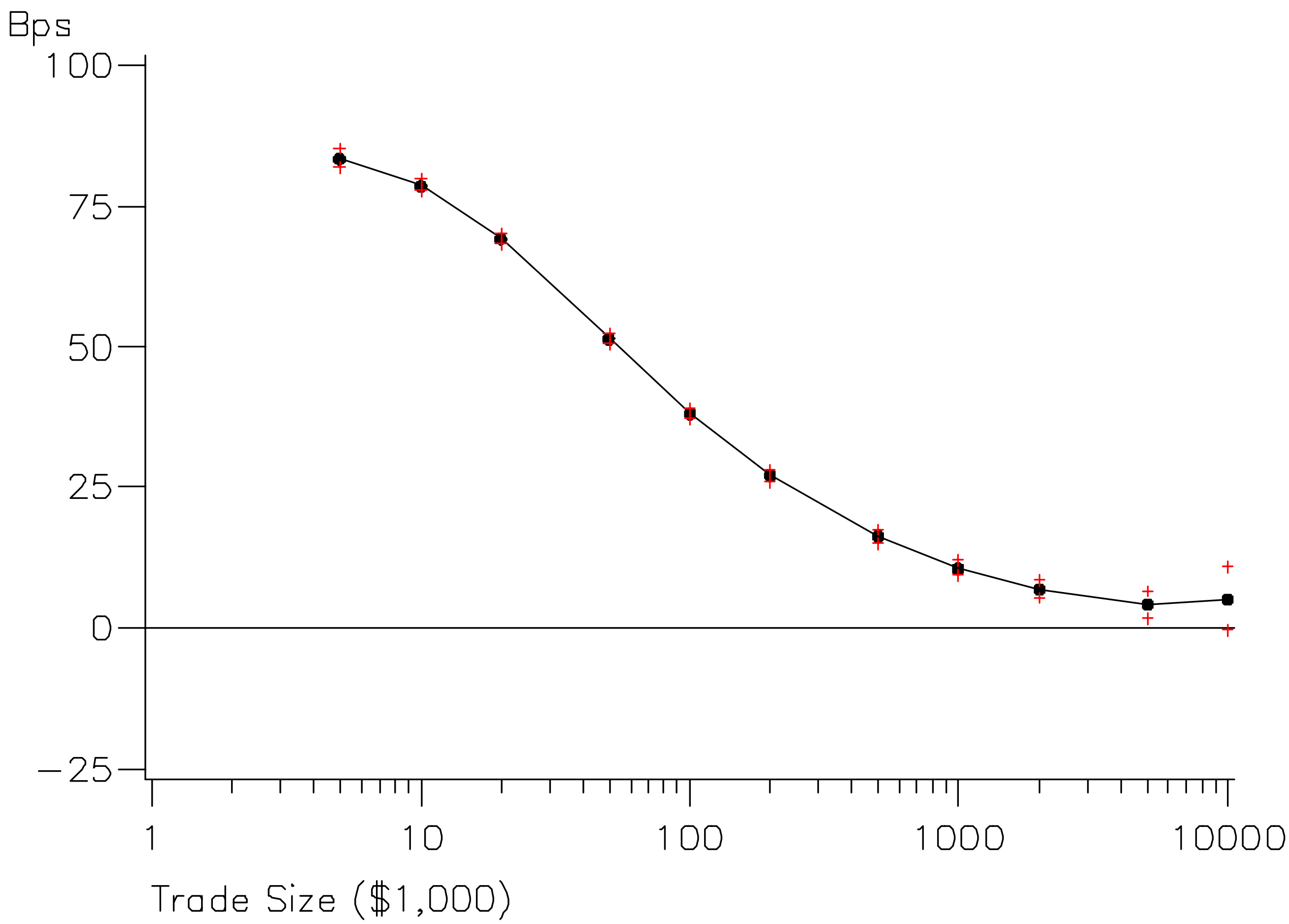


Figure 1: Mean estimated transaction costs by trade size. This figure presents weighted cross-sectional mean estimated corporate bond transaction costs (in basis points) for the entire sample. The cost estimates plotted on the solid line are computed from estimated coefficients obtained from the time-series regression of equation (7) for each bond using equation (10). The estimated costs are effective half-spreads. The weights are given by the inverse of the cost estimate error variance that appears in (11). The points on either side of estimated cost function represent the weighted means of the 95 percent confidence intervals for the individual bond cost estimates. (Confidence intervals for the weighted mean estimates are indistinguishably different from the means for all but the largest trade sizes due to the large number of bonds in the sample.)

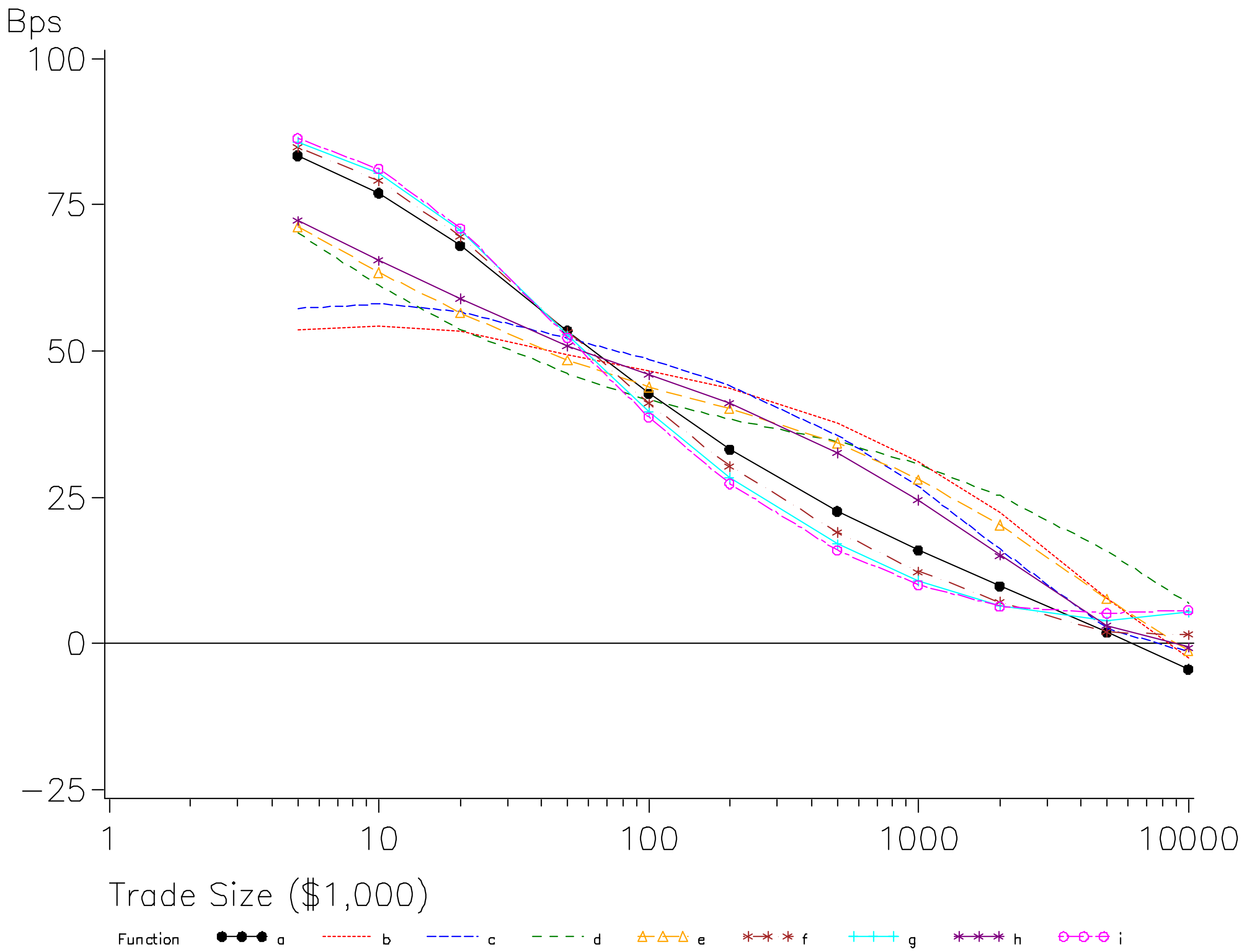


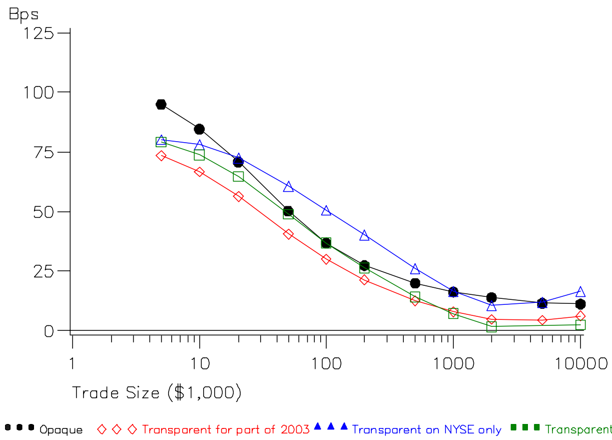
Figure 2: Mean estimated transaction costs for different cost function specifications. This figure presents cross-sectional weighted mean estimated municipal bond transaction costs (in basis points) for the entire bond sample for six different average cost function specifications. The different function forms include

$$c(S_t) = c_0 + c_1 \frac{1}{S_t} + c_2 \log S_t + c_3 S_t + c_4 S_t^2 + c_5 S_t^3$$

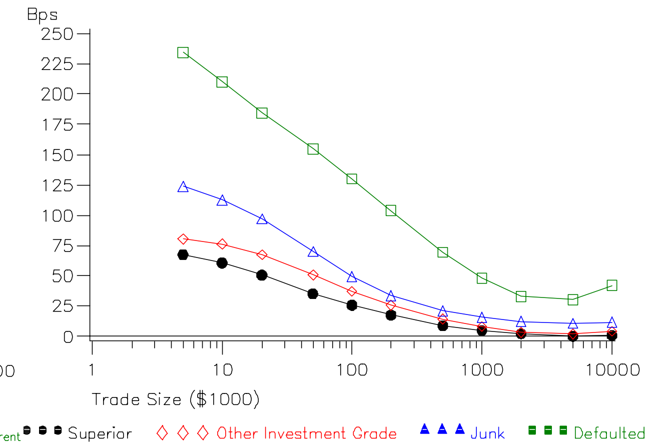
and nested models obtained by setting coefficients equal to zero as follows:

	Model								
Coefficient	a	b	c	d	e	f	g	h	i
c_1		0	0						
c_2		0	0	0	0			0	
c_3	0								
c_4	0			0		0			
c_5	0	0		0	0	0	0		

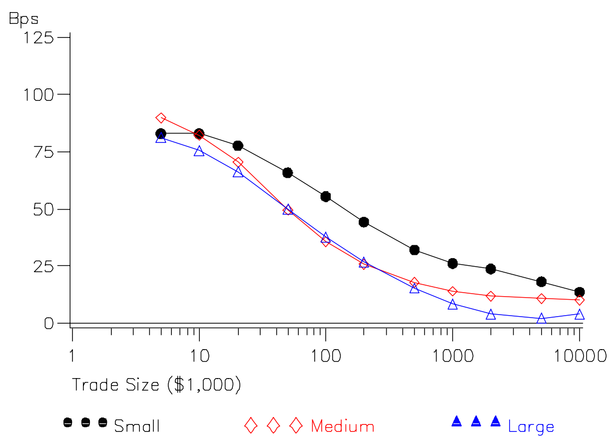
The cost estimates for the time-series regression of equation (7) for each bond using equation (10). The estimated costs are effective half-spreads. The weights are given by the inverse of the cost estimate error variance that appears in (11). The model used throughout the paper is model G.



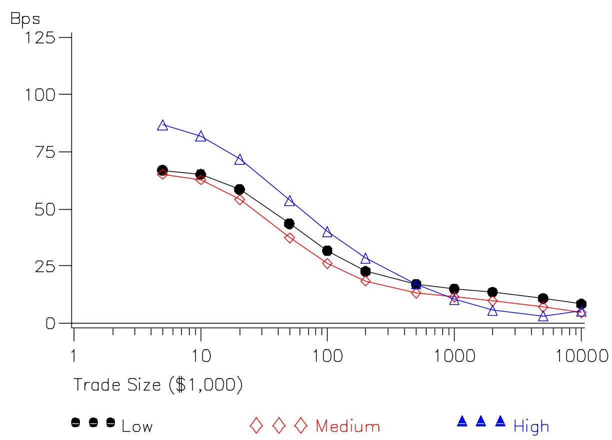
Panel A: Transparency classes



Panel B: Credit rating classes



Panel C: Issue size classes



Panel D: Trading activity classes

Figure 3. Mean estimated transaction costs for various bond classifications. This figure presents weighted cross-sectional mean estimated corporate bond transaction costs (in basis points) computed separately for various bond classifications. The cost estimates are computed from estimated coefficients obtained from the time-series regression of equation (7) for each bond using equation (10). The estimated costs are effective half-spreads. The weights are given by the inverse of the cost estimate error variance that appears in (11). Bonds in the low, medium, high, and very high trade activity classes respectively have 1 or fewer transactions per week; between 1 transaction per week and 1 transaction per day, and more than 1transaction per day. Bonds in the superior, other investment, and speculative credit quality classes respectively include bonds rated AA and above, BBB to A, and below BBB. The small, medium and large issue size classes respectively include bonds smaller than one hundred million dollars, between 100 and 500 million dollars, and above 500 million dollars.