WILEY

Corporate Bond Market Transaction Costs and Transparency

Author(s): Amy K. Edwards, Lawrence E. Harris and Michael S. Piwowar

Source: *The Journal of Finance*, Jun., 2007, Vol. 62, No. 3 (Jun., 2007), pp. 1421-1451
Published by: Wiley for the American Finance Association
Stable URL: https://www.jstor.org/stable/4622305

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at https://about.jstor.org/terms

and *Wiley* are collaborating with JSTOR to digitize, preserve and extend access to *The Journal of Finance*

JSTOR

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

THE JOURNAL OF FINANCE • VOL. LXII, NO. 3 • JUNE 2007

Corporate Bond Market Transaction Costs and Transparency

AMY K. EDWARDS, LAWRENCE E. HARRIS, and MICHAEL S. PIWOWAR*

ABSTRACT

Using a complete record of U.S. over-the-counter (OTC) secondary trades in corporate bonds, we estimate average transaction costs as a function of trade size for each bond that traded more than nine times between January 2003 and January 2005. We find that transaction costs decrease significantly with trade size. Highly rated bonds, recently issued bonds, and bonds close to maturity have lower transaction costs than do other bonds. Costs are lower for bonds with transparent trade prices, and they drop when the TRACE system starts to publicly disseminate their prices. The results suggest that public traders benefit significantly from price transparency.

SECONDARY TRANSACTION 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 United States—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 between January 2003 and January 2005.

Bond transaction costs are not well known because corporate bond markets are not nearly as transparent as are equity markets.[1] Dealers provide public

*Amy Edwards is a Financial Economist in the Office of Economic Analysis of the U.S. Securities and Exchange Commission. Larry Harris is the Fred V. Keenan Chair at the Marshall School of Business, University of Southern California. Mike Piwowar is a Principal at Securities Litigation and Consulting Group, Inc. Much of this research was completed while Dr. Harris was Chief Economist and Dr. Piwowar was a Financial Economist at the SEC. The paper has benefited from the comments of the editor (Rob Stambaugh), an anonymous referee, Chester Spatt, Lisa Hasday, Yolanda Goettsch, Bruno Biais, Pam Moulton, Gideon Saar, and Hank Bessembinder. We thank seminar participants at the SEC, the University of Delaware, George Washington University, Barclays Global Investors, Arizona State University, Emory University, Hofstra University, University College Dublin, Federal Reserve Board of Governors, George Mason University, and American University. We also thank conference participants at the Q Group Fall 2004 Research Seminar, the 2004 Bank of Canada Fixed Income Workshop, the 2005 Utah Winter Finance Conference, the 2005 Moody's and London Business School Credit Risk Conference, and the 2005 Western Finance Association Annual Meeting. The Securities and Exchange Commission disclaims responsibility for any private publication or statement of any SEC employee. This study expresses the authors' views and does not necessarily reflect those of the Commission, the Commissioners, or other members of the staff. All errors and omissions are the sole responsibility of the authors.

[1] See Biais and Green (2005) for a history and an overview of the structures of the U.S. corporate and municipal bond markets.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

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 transaction 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 transaction costs when deciding how to structure their bonds. Bond features that reduce liquidity are unattractive to investors and therefore costly to issuers.[2] Regulators study transaction costs to determine how these costs depend on market structure, and in particular, on price transparency. Understanding such relations allows the regulators to adopt polices that promote competition and efficiency.

We find that secondary transaction costs in the corporate bond market decrease with trade size. Specifically, our round-trip transaction cost estimates range from about 150 basis points (bps) for the smallest trade sizes to about three bps for the largest trade sizes. Our cross-sectional results reveal that transaction costs increase in credit risk and decrease in issue size. A bond's transaction costs are lowest when the bond is just issued and again when it is about to mature. Bonds issued in private placements with restricted trading (Rule 144a) have much smaller transaction costs, suggesting why these issuances are so popular. Global and foreign bonds have lower transaction costs than domestically issued bonds of U.S. corporations.

U.S. bond markets are becoming increasingly transparent. The National Association of Securities Dealers (NASD) now requires dealers to report all over-the-counter (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 has phased in real-time dissemination of these prices to the public. By the end of our sample period, prices from about 99% of all trades representing about 95% of the dollar value traded were disseminated within 15 minutes.[3] The Bond Market Association, the trade organization for bond dealers, questions whether all bonds should be transparent, citing concerns that transparency will hurt liquidity.[4] The results of this study should help inform the debate over the effect of transparency on liquidity. We find that transaction 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

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

[3] See SEC Release No. 34-49920; File No. SR-NASD-2004-094. This figure does not include the trades of the Rule 144a market, which is still opaque.

[4] 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.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

results as evidence that transparency has improved liquidity in corporate bond markets.

Our results suggest that transparency decreases customer transaction costs by roughly five basis points. Our data show 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 could have saved a minimum of $1 billion per year if the prices of all bonds had been TRACE-transparent. This figure represents a lower bound on the full cost savings from transparency for at least two reasons.

First, in a related study, Bessembinder, Maxwell, and Venkataraman (2006) find a reduction in transaction costs at the initiation of TRACE in July 2002 for a group of relatively sophisticated institutional traders (insurance companies). We do not capture this initial reduction in transaction costs in our analysis, which Bessembinder et al. (2006) estimate to be roughly $1 billion per year for institutions.

Second, learning how to obtain, organize, and use price data takes time for less sophisticated traders. Accordingly, we are not likely to observe the full effect of transparency on transaction costs right away. 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 underestimate the ultimate total cost savings.

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

I. Related Literature

A. Transaction Costs

Our contributions to the transaction costs literature follow from two methodological choices. First, our findings are based upon a more comprehensive data set than the related literature. Our study is the first to utilize the full transaction data from the NASD's TRACE system. The TRACE data consist of all OTC transactions in corporate bonds. In contrast, other research relies on data sets of transactions that correspond to a subset of institutions (e.g., Bessembinder et al. (2006) use Capital Access International data to study insurance company trades) or a subset of bonds (e.g., Goldstein, Hotchkiss, and Sirri (2006) use TRACE, but examine BBB-rated corporate bonds only).

Second, our transaction cost estimation methods differ from those used in earlier studies of corporate bond transaction costs. Previous studies of such

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

costs employ 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 limiting in the context of corporate bonds, as the median number of trades per day is less than one. This approach eliminates most transactions when estimating bond transaction costs, and it cannot estimate transaction costs for many infrequently traded bonds. Thus, this type of estimator is not well suited for inactively traded securities, and in turn, 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. This 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. Bessembinder et al. (2006) estimate a variation of the Schultz (2001) model that incorporates company-specific information, which allows them to estimate transaction costs for high-yield bonds. Goldstein et al. (2006) use a method similar to Schultz (2001) to estimate transaction costs for a sample of BBB-rated bonds.

Harris and Piwowar (2006) develop a different regression approach to study the secondary transaction costs of municipal 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, in particular, the absence of firm bid and ask quotes, infrequent trading, and data indicators for dealer sales to customers, dealer purchases from customers, and interdealer transactions. We apply the Harris and Piwowar (2006) approach to corporate bonds and extend it by allowing liquidity to be time varying. This extension allows us to examine how the introduction of price transparency affects corporate bond transaction costs.[6]

Other studies examine how transaction costs are related to various cross-sectional bond features. Larger and newer issues have lower transaction costs (Chakravarty and Sarkar (2003), Hong and Warga (2000)). More complex municipal bonds (i.e., more difficult to value because they have attached call options, put options, sinking fund provisions, and/or nonstandard bond attributes) and a longer time to maturity are associated with higher transaction costs (Harris and Piwowar (2006)). Bonds from issuers in the utilities industry also have higher transaction costs (Chakravarty and Sarkar (2003)). Some studies find that higher credit risk is linked to higher transaction costs (Harris and Piwowar (2006), Chakravarty and Sarkar (2003), and Hong and Warga

[5] See also Green, Hollifield, and Schürhoff (2004) and Kalimipalli and Warga (2002).

[6] Harris and Piwowar (2006) 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.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

(2000)). Schultz (2001) does not find a relation between credit risk and transaction costs. The results on the effect of having publicly traded equity are similarly mixed (Alexander, Edwards, and Ferri (2000) and Hotchkiss, Warga, and Jostova (2002)).

Our analysis incorporates all of these previously examined bond features, plus two additional ones. We include in our cross-sectional transaction cost analysis whether a bond's trading is restricted (Rule 144a) and whether the bond is a global or a foreign-issuer's bond. Because Rule 144a bonds trade in a market that is restricted to large institutions and the disclosure requirements for the issues are lower, we expect the transaction costs of Rule 144a bonds to differ from fully registered bonds (see Fenn (2000)). Because other studies find that cross-border capital decisions affect liquidity (see Karolyi (2004)), we suspect that global and foreign bonds have different transaction costs from U.S. domestic bonds.

B. *Transparency*

The effect of transparency on liquidity is an important discussion topic among corporate and municipal bond market participants and regulators. Some argue that introducing price transparency to the bond markets will facilitate better deterrence and detection of fraud and manipulation and will improve pricing efficiency and competition in bond markets, leading to lower transaction costs.[7] Others contend that transparency will increase dealers' costs of providing liquidity, leading to less dealer participation, less competition, less liquidity, and ultimately higher transaction costs.[8] The academic literature on price transparency yields mixed predictions on the effect of changes in transparency (see O'Hara (1997), Madhavan (2000), and Biais, Glosten, and Spatt (2005)). To the best of our knowledge, no extant empirical study examines the introduction of price transparency to another secondary financial market. By examining the corporate bond market, a market in which price transparency has been added to a previously opaque market, we can advance our general understanding of transparency.

Our study shows that transparent bonds have lower transaction costs than nontransparent bonds, and that transaction costs decrease when bonds become price transparent. These results complement the results of at least three other studies. Alexander et al. (2000) find that transparent high-yield bonds can be fairly liquid. Bessembinder et al. (2006) find declines in transaction costs for insurance company trades in corporate bonds around the July 2002 introduction

[7] See, for example, "Testimony before The United States Senate Committee on Banking, Housing and Urban Affairs," Statement of Annette Nazareth, Director of the Division of Market Regulation, U.S. Securities and Exchange Commission, June 17, 2004 and the letter on bond market transparency from SEC Chairman Richard Breeden to Senator Donald Riegle dated September 6, 1991.

[8] 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 and the letter on bond market transparency from SEC Chairman Richard Breeden to Senator Donald Riegle dated September 6, 1991.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

of TRACE. Goldstein et al. (2006) find declines in transaction costs due to transparency for all but the smallest trade size groups in a matched-pair analysis of BBB bonds. However, because our analysis provides a much broader cross section of transactions and bond issues than the others, our conclusions are more broadly applicable.

II. Data and Sample

We obtain trades reported to TRACE between January 2003 and January 2005 (524 trading days). The TRACE data set includes all reported OTC trades in corporate bonds, whether transparent or not. 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.[9] Our TRACE data also include issuer and issue information in the form of 18 master file snapshots taken at various points in time during the sample period.

The only trades omitted from TRACE are those that occurred on exchanges, of which the vast majority occur on the NYSE's Automated Bond System (ABS). Fewer than 5% of all bonds are listed on the NYSE. For those bonds, ABS trades, which are almost all small retail trades, represent from zero to 40% of all transactions. Thus, the TRACE data set contains almost all corporate bond trades.

The NASD started collecting the TRACE data set on July 1, 2002. Our analysis begins with January 2003 data, to allow market participants time to familiarize themselves with the system, and ends with January 2005 data. Table I describes the sample selection procedures. Over our sample period, the TRACE data identify 40,508 securities in which dealers must report their trades. Focusing on nonconvertible bonds, dealers reported 17.3 million trades, for a total volume of 19.8 trillion dollars, in 30,171 of these securities. We delete trade reports that were subsequently corrected, that appear to be incorrectly reported,[10] that are missing key information, that were reported by multiple dealers, and that were reported for bonds that are not identified in our transaction cost model.[11] The final sample consists of 12,320,016 trades, representing 9.3 trillion dollars of volume, in 21,973 bonds. The reductions in total number of trades, volume, and number of bonds are mostly due, respectively, to duplicate interdealer reports, corrected trades, and unidentified regressions.

[9] Transaction prices do not reflect the accrued interest from the coupons.

[10] 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 in which prices changed substantially between transactions that occurred weeks apart. To avoid this problem, we design two types of filters that operate on deviations from median prices and price reversals.

[11] Identification of our model 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 are not identified. For example, if all reported trades for a bond were purchases, the cost regression would not be identified.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Table I
Sample Composition

This table describes the effects of the various filters used to construct our final sample. Transaction data are taken from the complete January 2003 through January 2005 TRACE transaction data set. Security characteristic data are taken from 18 snapshots of the TRACE master file supplied by the NASD for the same period. The master files contain some securities that are identified as "active" (i.e., eligible to trade), but do not have any reported transactions during our sample period. We delete convertible issues and issues without all necessary information in the master files. We filter corrected trades, trades reported with a size that is not an integer, trades reported with an execution date prior to the TRACE "First Active Date," trades reported with an execution date after the maturity date, and trades reported with a size greater than half of the total issue size. We apply price filters based on deviations from median prices and price reversals to identify likely data entry errors while allowing for reasonable price changes. Since TRACE requires both dealers to report interdealer trades, we delete duplicate records of interdealer trades. Our final sample consists of bonds that have enough observations to identify the transaction cost regression model.

	Bonds	Trades	Dollar Volume (Billions)
All active issues listed in the TRACE master files	40,508	17,327,033	19,810
Subtotal after removing issues with missing information, convertible bonds, and "active" bonds that did not trade	28,192	16,352,523	18,269
Subtotal after filtering trades	27,342	14,727,661	10,857
Subtotal after removing duplicate interdealer trades	27,342	12,352,316	9,375
Final sample after applying transaction cost regressions	21,973	12,320,016	9,301

The median issuer in the sample has two bonds outstanding. This distribution, like many cross-sectional distributions, is skewed to the right. The average number of issues outstanding per issuer is more than nine. The average original issue size is $213 million and the average issuer has about $1.95 billion total outstanding. Bonds have an average of 8.4 years to maturity at issuance and have been around for 3.1 years on average. The average coupon in the sample is 6.2% and the average bond price in the sample is 100.6% of par.

Table II describes the trading activity of our sample bonds. On average, bonds traded only 2.4 times per day. The median trade rate is only 1.1 times per day. Because we require a minimum number of trades, our sample volume is not representative of the population. If we include all bonds, the median trade rate would be less than one trade per day. Trades are also clustered. The median bond trades on 48% of all days in the sample. The total number of dealers reporting trades also varies substantially across bonds. The sample median is 26 dealers.

Perhaps the most surprising statistic is that of the high sample turnover. The median turnover is 80% and the average is 119%. However, these results are consistent with turnover results reported in Alexander et al. (2000). The prevalence of small transaction sizes is also surprising. More than 40% of the customer trades are in retail-sized transactions (less than 100,000 dollars), though most of the dollar volume is in institutional-sized trades.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Table II
Sample Trading 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 12.3 million trades in almost 21,973 corporate bonds. Unless otherwise noted, the statistics summarize means computed for each bond. Retail- and institutional-sized 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	2.4	0.1	1.1	19.5
Interdealer	0.7	0.0	0.3	6.7
Retail size customer	1.1	0.0	0.3	10.4
Institutional size customer	0.6	0.0	0.2	4.7
Mean dollar volume ($ thousand)	198.7	0.1	27.9	2,559.5
Interdealer	48.7	0.0	5.0	703.5
Retail size customer	2.4	0.0	0.8	22.7
Institutional size customer	147.6	0.0	13.3	1,783.8
Mean annualized turnover (%)	119.3	0.9	79.6	705.3
Interdealer	34.6	0.0	19.3	228.2
Retail size customer	10.8	0.0	2.9	64.0
Institutional size customer	73.9	0.0	32.5	495.0
Frequency of days with a trade (%)	52.7	2.7	48.0	100.0
Interdealer	40.9	0.0	22.5	100.0
Retail size customer	45.0	0.0	33.1	100.0
Institutional size customer	38.0	0.0	17.0	100.0
Trade size in value ($ thousand)	1,206.0	10.6	240.6	15,204.9
Minimum	30.4	0.5	2.0	549.5
Median	632.7	6.1	26.6	10,000.0
Maximum	13,781.2	28.1	4,579.6	133,477.8
Interdealer	897.0	9.0	164.1	11,193.7
Retail size customer	25.2	6.1	21.6	72.3
Institutional size customer	1,937.4	97.2	1,146.3	17,817.0
Simple statistics across trades	757.2	1.1	29.7	10,629.3
Mean number of dealers	42.8	2.0	26.0	245.0
Interdealer	22.7	1.0	14.0	137.0
Retail size customer	14.8	1.0	9.0	92.0
Institutional size customer	9.8	1.0	7.0	43.0

A. Bond Classifications

Our cross-sectional analyses examine how bond transaction costs depend on numerous bond features. To provide context for the results, we characterize these bond characteristics in Table III.

The NASD phased in transparency on 3 days during our sample period: March 3, 2003, April 14, 2003, and October 1, 2004.[12] Accordingly, some bonds were

[12] The NASD altered transparency for a small group of bonds on five other dates during our sample period. These changes involved revising the list of 50 transparent high yield bonds (the "TRACE 50," formerly the "FIPS 50"). This involved some transparent bonds becoming opaque and some opaque bonds becoming transparent. These minor transparency changes are accounted for in our cross-sectional tests. See Alexander, Edwards, and Ferri (2000) for a discussion of the criteria for the FIPS 50.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Table III

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 the sample period (January 2003 to January 2005). Credit quality is based on the average credit quality during the sample period. A bond is classified as defaulted if it was in default at any point in the sample period. The bonds are classified into age categories based on their average age in the sample period. 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 bond's issuer has publicly traded equity in the U.S. 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	15,273	69.5	11,082	90.0	7,808	83.9
ABS-listed	431	2.0	494	4.0	275	3.0
Both ABS and TRACE	335	1.5	463	3.8	267	2.9
Not transparent	6,598	30.0	1,206	9.8	1,485	16.0
Credit quality						
Superior (AA and up)	2,547	11.6	1,088	8.8	813	8.7
Other investment grade (BBB-A)	14,373	65.4	7,812	63.4	5,459	58.7
High yield (below BBB)	4,842	22.0	3,117	25.3	2,816	30.3
Not rated	382	1.7	51	0.4	47	0.5
Defaulted	547	2.5	252	2.0	167	1.8
Issue size						
Small (<$100 million)	10,306	46.9	1,807	14.7	117	1.3
Medium ($100 to $500 million)	9,158	41.7	4,061	33.0	2,909	31.3
Large (>$500 million)	2,581	11.7	6,452	52.4	6,275	67.5
Age						
0–3 months	3,792	17.3	567	4.6	744	8.0
3–6 months	2,305	10.5	697	5.7	853	9.2
6 months–1 year	3,349	15.2	2,046	16.6	1,947	20.9
1 year–one-half life	6,780	30.9	5,884	47.8	4,089	44.0
One-half life–maturity	5,747	26.2	3,125	25.4	1,668	17.9
Industry						
Finance	12,461	56.7	5,990	48.6	3,900	41.9
Utilities	6,973	31.7	5,266	42.7	4,377	47.1
Other	2,689	12.2	1,064	8.6	1,025	11.0
Equity status						
Publicly traded in United States	18,523	84.3	11,429	92.8	8,347	89.7
Private or foreign	3,450	15.7	891	7.2	954	10.3
Bond complexity features						
Callable	7,389	33.6	2,695	21.9	1,375	14.8
Noncash call	573	2.6	182	1.5	123	1.3
Soon to be called	1,256	5.7	46	0.4	16	0.2
Putable	394	1.8	78	0.6	87	0.9
Sinking fund	392	1.8	49	0.4	69	0.7
Floating rate coupon	1,527	6.9	189	1.5	723	7.8
Variable rate coupon	680	3.1	235	1.9	253	2.7
Combination of floating/fixed	74	0.3	9	0.1	12	0.1
Nonstandard payment frequency	5,712	26.0	1,196	9.7	802	8.6
Nonstandard accrual frequency	1,579	7.2	749	6.1	1,122	12.1
Type of issue						
Global	3,366	15.3	5,408	43.9	4,772	51.3
Foreign	1,030	4.7	329	2.7	465	5.0
Rule 144a issue	2,158	9.8	460	3.7	1,076	11.6

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

TRACE-transparent for only a portion of the sample period. 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, almost 70% were TRACE-transparent at some point between January 2003 and January 2005. These bonds represent 90% of all trades and 84% of all dollar volume.

Our TRACE sample includes 431 bonds that are listed on the NYSE's Automated Bond System (ABS). All ABS trades are transparent. In addition, ABS offers pre-trade transparency in the form of displayed limit orders. TRACE-reported trades in listed bonds represent 4% of our sample and 3% of the total dollar volume. A small number of bonds are both TRACE-transparent and ABS-listed, while 30% of bonds, 10% of the trades, and 16% of the dollar volume were not transparent at all. Nontransparent bonds include Rule 144a bonds, matured bonds, bonds that did not trade after becoming transparent, and a small number of bonds that were still not transparent at the end of the sample period.

Using S&P and Moody's ratings from the TRACE master files, we assign bond ratings to a common numeric scale that ranges from 1 for bonds in default to 25 for AAA bonds. We estimate the average rating across both agencies and time to quantify credit quality for each bond, after adjusting for average differences among the agencies.

Table III classifies each bond into four grades based on its average rating: Superior (AA and above), all other investment grade (BBB to A), high yield (below BBB), and in default. The superior category includes 12% of the bonds, 9% of the trades, and 9% of the total value trade in the sample. Most of the remainder appears in the other investment grade category. High-yield bonds represent 22% of the bonds in the sample, 25% of the trades, and 30% of the volume. Unfortunately, about 2% of the bonds in the sample, representing 0.4% of the trades and 0.5% of the total value traded, are unrated. Two-and-a-half percent of the sample bonds were in default at some point in our sample period.

We also classify bonds into three issue size categories. Small bond issue sizes (less than $100 million) account for 47% of the number of our sample bonds, but only 15% and 1% of the number of trades and the total value traded, respectively. About 42% of the bonds in the sample fall into the medium ($100 million to $500 million) issue size category. Large bond issue sizes (greater than $500 million) account for only 12% of the number of sample bonds, but 52% and 68% of the number of trades and the total value traded, respectively.

The average age of the sample bonds is fairly low. Seventeen percent of the bonds have an average age of less than 3 months. Most of the trades (48%) and volume (44%) occur in bonds aged between 1 year and one half of the original time to maturity. As expected, bonds that are near the end of their life (26% of bonds) trade less frequently (25% of trades and 18% of volume) than do other bonds.

The apparent decline in a bond's trading volume over time is consistent with the well-known "on-the-run" phenomenon documented for Treasury securities, whereby bonds from the most recent Treasury auction ("on-the-run" securities)

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

are more liquid than other, similar bonds. However, the magnitude of the decline in the corporate bond market is much smaller than the decline in the Treasury market, where volume drops by 90% when a bond goes "off-the-run" (Barclay, Hendershott, and Kotz (2006)). Previous studies (Warga (1992) and Alexander et al. (2000)) estimate that corporate bonds take about 2 years to settle into institutional portfolios, after which point the secondary market is thinner but still alive.

While companies from a wide array of industries issue bonds, most bonds that trade are classified as Finance (57%) or Utilities (32%). We therefore divide the bonds into three industry categories: Finance, Utilities, and Other.

Some privately held companies issue publicly traded debt.[13] 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 (CRSP) data set and on the OTC Bulletin Board web site. We then group subsidiaries of public companies with their parents. In addition, some issuers may have publicly traded equity in other countries. We do not attempt to identify these issuers; rather, we combine them with the private companies. In total, we classify only 15.7% of the sample bonds as private. Private companies represent an even smaller percentage of trades (7%) and volume (10%). These totals are well below the percentage of private companies reported in Hotchkiss et al. (2002). The discrepancy may be due to issuers' use of multiple CUSIP numbers.[14]

We characterize bond complexity using features that complicate bond valuation. About 34% of our sample bonds are callable, which means that the issuer can redeem them before the maturity date under stated conditions. A small number of sample bonds (2.6%) have calls that are payable in something other than cash. Some bonds in the sample are putable (1.8%).

We classify coupon 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.

Sinking fund provisions require the issuer to retire a specified portion of debt each year by purchasing it on the open market. About 1.8% of our bonds have sinking fund provisions. Nonstandard interest payment frequency bonds pay interest at frequencies other than semiannual. About 26% 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 7% of our sample bonds have nonstandard interest accrual methods.

III. Average Bond Transaction Cost Estimation Methods

Corporate bond data present two challenges for transaction cost measurement. First, since quotation data generally do not exist for most of the corporate

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

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

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

bond market, we cannot estimate transaction costs for each trade using transaction methods based on benchmark prices such as the effective spread. Instead, we estimate transaction costs using an econometric model.

The second problem relates 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 if such information were available. Accordingly, we 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.

A. The Time-Series Estimation Model

We estimate transaction costs using the econometric model developed in Harris and Piwowar (2006). To conserve space, we only briefly describe their 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 a 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 (costs as a fraction of price) and total dollar trade value because these are the 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 whether the customer is a buyer ($Q_t = 1$), a seller ($Q_t = -1$), or not present (i.e., interdealer trade; ($Q_t = 0$)), and I_t^D to indicate whether the trade is an interdealer trade ($I_t^D = 1$) or not ($I_t^D = 0$) gives

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

Taking logs of both sides, making two small approximations, subtracting the same expression for trade s, and dropping the approximation sign yields

$$r_{ts}^P = r_{ts}^V + Q_t c(S_t) - Q_s c(S_s) + I_t^D \delta_t - I_s^D \delta_s, \tag{2}$$

where r_{ts}^P is the continuously compounded observed bond price return between trades t and s, and r_{ts}^V is the unobserved value return between trades t and s.

Following Harris and Piwowar, we model the unobserved 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

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

for high and low credit risk bonds, and a bond-specific valuation factor, ε_{ts}.[15] Specifically,

$$r_{ts}^{V} = Days_{ts}(DriftRate) + \beta_1 AveIndexRet_{ts} + \beta_2 DurationDif_{ts} + \beta_3 CreditDif_{ts} + \varepsilon_{ts}, \tag{3}$$

where $Days_{ts}$ counts the number of calendar days between trades t and s, *DriftRate* is the bond coupon rate subtracted from 5%, $AveIndexRet_{ts}$ 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 credit risk bonds. The first term accounts for the continuously compounded bond price return that traders expect when interest rates are constant and the bond's coupon interest rate differs from 5%. The three factor returns account 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

$$\sigma_{\varepsilon_{ts}}^2 = N_{ts}^{Sessions} \sigma_{Sessions}^2, \tag{4}$$

where $N_{ts}^{Sessions}$ is the number of trading sessions between trades t and s.

We model customer transaction costs using the following additive expression:

$$c(S_t) = c_0 + c_1 \frac{1}{S_t} + c_2 \log S_t + c_3 S_t + c_4 S_t^2 + \kappa_t, \tag{5}$$

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 represent average transaction costs for all trade sizes. We assume κ_t has zero mean and variance given by σ_κ^2.

The five terms of the cost function together define a response function curve for average transaction costs. The constant term allows total transaction costs to grow in proportion to size, setting 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 specify and estimate several other versions of

[15] All bond returns in this study are expressed in terms of the equivalent continuously compounded return to a 5% notional bond. Since we compute the index returns using the same convention, the specification of 5% 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 indices into return models.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

the cost function. We discuss these alternatives and present their estimates in Section IV and Figure 2.

Combining equations (3), (4), and (5) produces our version of the Harris and Piwowar transaction cost estimation model:

$$\begin{aligned} & r_{ts}^P - Days_{ts}(DriftRate) \\ & \quad = c_0(Q_t - Q_s) + c_1\left(Q_t \frac{1}{S_t} - Q_s \frac{1}{S_s}\right) + c_2(Q_t \log S_t - Q_s \log S_s) \\ & \qquad + c_3(Q_t S_t - Q_s S_s) + c_4\left(Q_t S_t^2 - Q_s S_s^2\right) \\ & \qquad + \beta_1 AveIndexRet_{ts} + \beta_2 DurationDif_{ts} + \beta_3 CreditDif_{ts} + \eta_{ts}, \end{aligned} \tag{6}$$

where the left-hand side is simply the continuously compounded bond return expressed as the equivalent rate on a notional 5% coupon bond, and

$$\eta_{ts} = \varepsilon_{ts} + Q_t \kappa_t - Q_s \kappa_s + I_t^D \delta_t - I_s^D \delta_s \tag{7}$$

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

$$\sigma_{ts}^2 = N_{ts}^{Sessions} \sigma_{Sessions}^2 + D_{ts} \sigma_\delta^2 + (2 - D_{ts}) \sigma_\kappa^2, \tag{8}$$

where D_{ts} equals zero, one, or two to represent the number of interdealer trades.

We estimate this model using the iterated weighted least-squares method described in Harris and Piwowar (2006) to ensure that we give the greatest weights to trade pairs from which we expect to learn the most about transaction costs. Because our econometric model requires that a bond trade at least nine times, our estimates of transaction costs might not be representative of less active bonds. Furthermore, our averages might be biased downward if the decision to trade is endogenous and dependent on transaction costs.

Table I shows that 20% (5,369 out of 27,342) of the bonds that pass all of the data filters are not actively traded enough to make it through our econometric model. However, we believe that our model minimizes these concerns relative to other models, especially since no existing model can estimate transaction costs without trades or firm quotations. Furthermore, in formulating the terms of the model, we optimize our cost estimates by finding the most parsimonious model, that is, the lowest-term model that approximates models with more terms. We are therefore able to include more than 99% of the filtered number of transactions and total valued traded without sacrificing the accuracy of the model. Nonetheless, we urge caution in extrapolating cost estimates out of sample for the least active bonds.

[17] The Harris and Piwowar (2006) 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, whereas they only employ a two-factor model.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

B. The Cross-Sectional Methods

Our cross-sectional analyses consider how estimated transaction costs vary across bonds for trades of 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, that is,

$$\hat{c}(S) = \hat{c}_0 + \hat{c}_1 \frac{1}{S} + \hat{c}_2 \log S + \hat{c}_3 S + \hat{c}_4 S^2. \tag{9}$$

The estimated error variance of this estimate is given by

$$\operatorname{Var}(\hat{c}(S)) = \mathbf{D}\hat{\Sigma}_{\hat{c}}\mathbf{D}', \tag{10}$$

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

$$\mathbf{D} = \begin{bmatrix} 1 & \dfrac{1}{S} & \log S & S & S^2 \end{bmatrix}. \tag{11}$$

The linear combination of the coefficients 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 regression models to relate the estimated costs computed from (9) to various bond characteristics. We estimate weighted least-squares regressions in which the weights are given by the inverse of the cost estimate error variance in (10). 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 large and the bond will have essentially no effect on the results. This may result if the time-series regression is overidentified 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 therefore allows us to endogenously choose the appropriate cross-sectional sample for our various analyses.[18]

[18] As noted by Harris and Piwowar (2006), 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 barely identified. To avoid this problem, we use the Bayesian shrinkage estimator introduced in the appendix to Harris and Piwowar (2006) to estimate regression mean-squared errors.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

IV. Time-Series Results

We estimate the transaction cost model (6) separately for each sample bond. Average customer transaction costs should be positive since customers in dealer markets generally pay the bid–ask spread when trading. Table IV 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 and because large trades are less costly than small trades. As a result, estimates are less accurate at such sizes.

Figure 1 plots cross-sectional mean cost estimates across the sample bonds, 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% confidence intervals

Table IV

Estimated Costs

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

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

The dependent variable is the continuously compounded return—expressed as the equivalent return to a notional 5% bond—between trades. $Days_{ts}$ 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 separately for each of the 21,973 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 (%)	Weighted Mean Slope of the Cost Function (Basis Points per $1,000)
5	75	60	88.1	−0.01
10	71	56	91.2	−0.01
20	62	48	92.1	−0.01
50	46	33	91.2	−0.002
100	34	24	88.3	−0.001
200	24	17	82.8	−0.001
500	14	10	76.5	−0.0002
1,000	9	6	71.7	−0.0001
2,000	5	3	67.2	<−0.0001
5,000	3	1	65.3	<0.0001
10,000	4	1	61.6	<0.0001

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

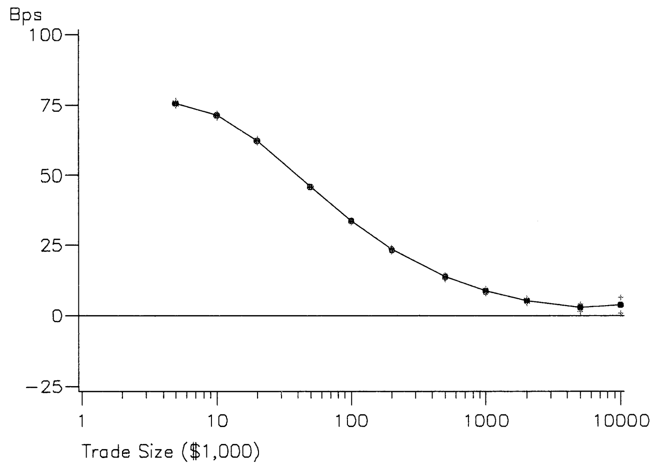

Figure 1. Mean estimated transaction costs by trade size. This figure presents weighted cross-sectional mean estimated corporate bond transaction costs (in basis points) for the entire sample. The cost estimates plotted on the solid line are computed from estimated coefficients obtained from the time-series regression of equation (6) for each bond using equation (9). The estimated costs are effective half-spreads. The weights are given by the inverse of the cost estimate error variance that appears in (10). The points on either side of estimated cost function represent the weighted means of the 95% 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.)

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 is 1.24% of price (62 bps $\times$ 2), while the average round-trip cost for a representative institutional order size of $200,000 is only 0.48% (24 bps $\times$ 2).[20] These results may indicate that institutional traders generally negotiate better prices than do retail traders, or that dealers price their trades to cover fixed trading costs.

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

$$\hat{c} = a_0 + a_1 \frac{1}{S} \tag{12}$$

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

[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.

[20] Our transaction cost measures estimate effective half-spreads. Thus, a cost of 62 basis points represents an effective spread of 124 basis points.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

size were simply due to spreading a fixed cost (a_1) over greater size, this line would closely fit the plotted average cost function. 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 IV 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 consistent with the results that Schultz (2001) and Bessembinder et al. (2006) find in their studies of insurance company trades in the U.S. corporate bond market. More broadly, it is also consistent with studies that document that dealer markets offer lower transaction costs to larger trades. See, for example, the Harris and Piwowar (2006) study of the U.S. municipal bond market and the Reiss and Werner (1996) and Bernhardt et al. (2005) studies of the London Stock Exchange. In particular, Bernhardt et al. (2005) argue that the observed discounts to large orders are due to dealers giving better prices to large clients with repeat business potential, and thus discouraging large clients from breaking up orders.

Effective spreads in equity markets for retail-sized trades average less than 40 basis points in contrast to the 124 basis points that we estimate for corporate bond trades of \$20,000. We cannot reasonably attribute this cost difference to adverse selection because equities generally are subject to much more credit risk than are corporate bonds. Moreover, 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. Dealers can also hedge credit risk using the issuer's equities. The only credible explanation for the cost difference is the market structure explanation, and the most important structural difference across the two markets is that of transparency.

The results we obtain for the January 2003 through January 2005 TRACE corporate bond sample are similar to those that Harris and Piwowar (2006) obtain for the 2000 MRSB municipal bond sample. In both cases, the estimated cost functions decline significantly with size. However, the estimated bond transaction costs are about 40% to 60% lower for the corporate bonds than for the municipal bonds of various sizes. The difference may be due to the different sample periods, to the fact that corporate bonds trade in more active and more transparent markets, or both.[21] The difference cannot be due to differences in credit quality since the average municipal bond is much more secure than the average corporate bond.

[21] 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. Chakravarty and Sarkar (2003) find that corporate and municipal transaction costs for insurance companies are about the same.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Our results are also close to those that Bessembinder et al. (2006) obtain for comparable transaction sizes. For their 2002 sample of insurance company trades with a mean transaction size of about \$3 million, the Bessembinder et al. (2006) results indicate one-way transaction costs of about six to seven bps. Our estimate for the \$2 million trade size is five bps and our estimate for the \$5 million trade size is three bps.[22]

To determine whether the average cost results depend on the functional form chosen for the cost function, we specify and estimate nine alternative functions, including

$$c(S_t) = c_0 + c_1 \frac{1}{S_t} + c_2 \log S_t + c_3 S_t + c_4 S_t^2 + c_5 S_t^3 \tag{13}$$

and various nested models obtained by setting different combinations of coefficients in (13) to zero. Figure 2 plots the nine estimated cost curves. The curves lie close to each other, which suggests that the average cost results do not depend much on the functional form chosen. The results reported in this study are based on the five-parameter model obtained by constraining c_5 to zero. We select this particular five-parameter model because it produces 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 choose a larger model because 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 four classification variables. Panel A plots the mean cost estimates for three transparency classes. The first plot compares bonds for which fewer than 50% of the transactions during the sample period were transparent to bonds for which most transactions were transparent. The relatively transparent bonds have lower transaction costs than the relatively opaque bonds across all trade sizes. The plot further distinguishes the relatively opaque bonds that were ABS-listed during the sample period. The listed bonds have lower transaction costs than the other relatively opaque bonds in the small trade sizes only. This result reflects the general perception that ABS is an odd-lot market in which 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 high-yield 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.

[22] When we restrict our sample period to only 2003, our estimate for the \$2 million trade size is seven bps and our estimate for the \$5 million, four bps.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

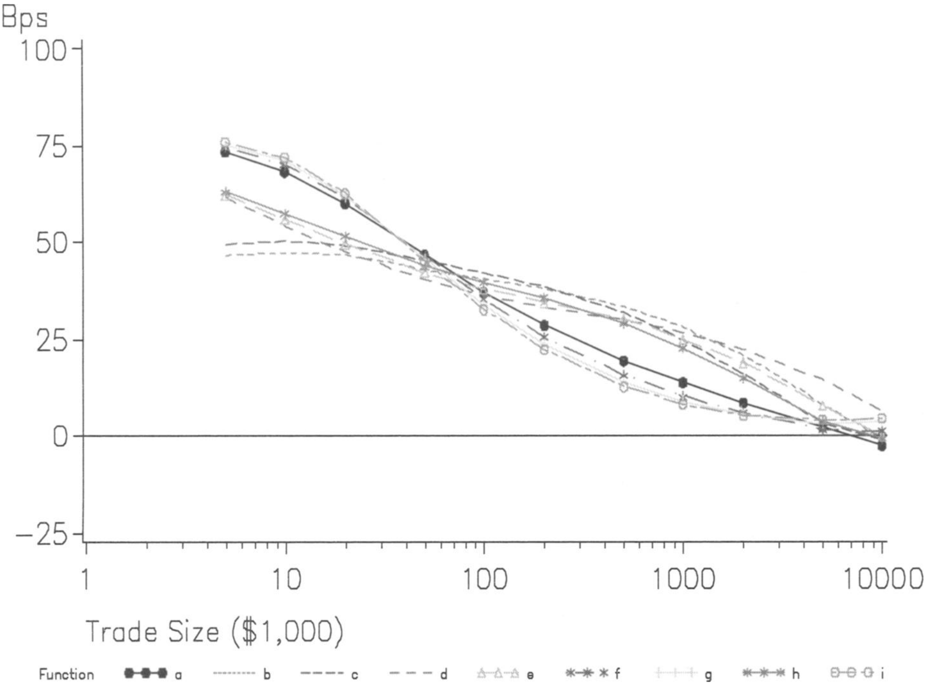

Figure 2. Mean estimated transaction costs for different cost function specifications. This figure presents cross-sectional weighted mean estimated municipal bond transaction costs (in basis points) for the entire bond sample for six different average cost function specifications. The different functional 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 (6) are computed for each bond using equation (9). The estimated costs are effective half-spreads. The weights are given by the inverse of the cost estimate error variance that appears in (10). The model used throughout the paper is model g.

Panel C plots mean cost estimates separately for small, medium, and large 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 in large and small trades, otherwise the costs of trading these two classes of bonds are quite similar.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

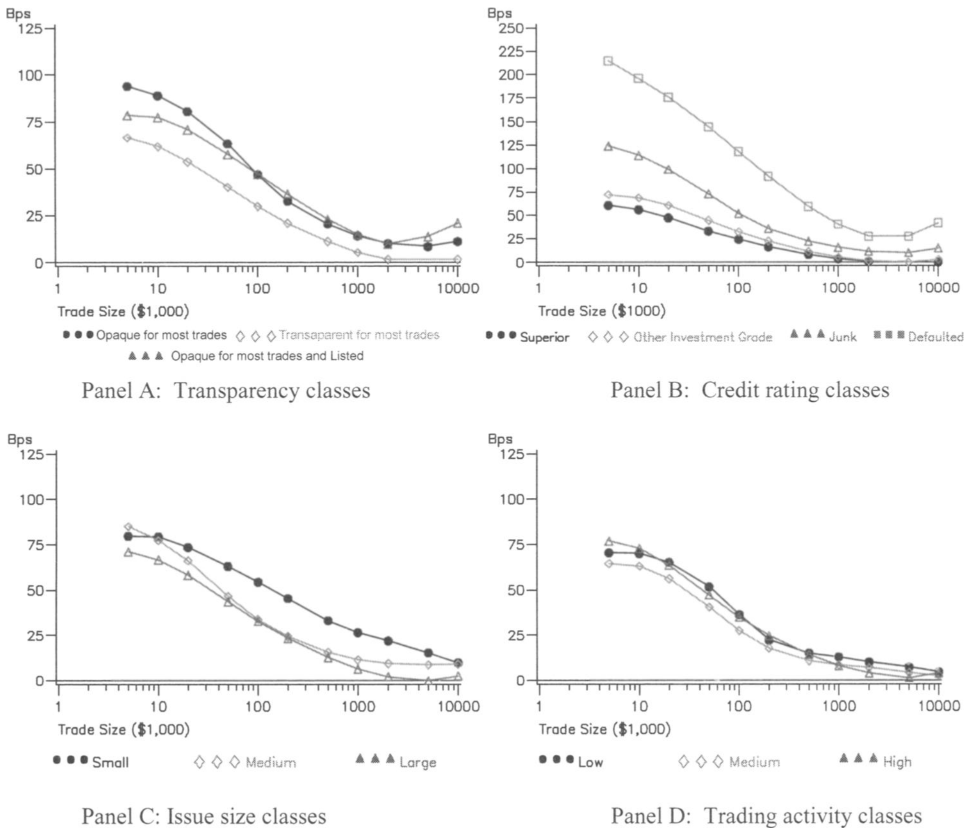

Figure 3. Mean estimated transaction costs for various bond classifications. This figure presents weighted cross-sectional mean estimated corporate bond transaction costs (in basis points) computed separately for various bond classifications. The cost estimates are computed from estimated coefficients obtained from the time-series regression of equation (6) for each bond using equation (9). The estimated costs are effective half-spreads. The weights are given by the inverse of the cost estimate error variance that appears in (10). Bonds in the low, medium, high, and very high trade activity classes, respectively, have one or fewer transactions per week, between one transaction per week and one transaction per day, and more than one transaction per day. Bonds in the superior, other investment, and high-yield (junk) 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 100 million dollars, between 100 and 500 million dollars, and above 500 million dollars.

Panel D presents results for three trading activity classes. Interestingly, transaction costs do not appear to be significantly related to trading activity. These results are surprising since costs are generally lower in active equity markets than in inactive equity markets.

The results reported in Figure 3 do not control for bond characteristics that may be correlated with trading activity, credit quality, issue size, or transparency. Because credit rating, issue size, and to a lesser degree, trading activity determine when a bond becomes transparent, we need to employ regression analysis to determine how transparency is associated with transaction

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

costs. The next section describes the regression analyses we use to identify the marginal contributions of these (and other) variables to total transaction costs.

V. Cross-Sectional Determinants of Transaction Costs

The dependent variables in our cross-sectional regressions are percentage transaction costs estimated for various representative trade sizes. The first set of results presented in Table V concern 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 a representative trade size of 20 bonds ($20,000), the effective half-spread for BBB bonds is 3.4 basis points more than that of bonds rated A and above. This difference rises to 18 basis points for high-yield bonds (B and BB) and to 44 basis points for distressed high-yield 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, which is probably a good proxy for poor credit quality. Bonds that defaulted during our period also cost more to trade.

The positive and highly significant coefficients on time since issuance indicate that newer bonds are less expensive to trade than older bonds. This result is consistent with well-known characteristics in the government bond markets in which the costs of trading on-the-run bonds are lower than the costs of trading seasoned issues.[23] However, Table III indicates that corporate bonds do not have nearly the on-the-run effect experienced by Treasury bonds.

The positive and highly significant coefficients on time to maturity indicate that bonds close to maturity are cheaper to trade than bonds that mature in the distant future. This could be due to the lack of interest rate risk at the end of the life of a bond. The negative and highly significant coefficients on dummy variables that represent bond features that decrease the expected time to maturity (i.e., soon-to-be-called bonds) corroborate these results.[24] 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.[25]

The regression includes inverse price as a regressor to determine whether corporate bond transaction costs have a fixed cost component. As expected, the estimated coefficients are positive and highly significant in all of the trade size regressions. The estimates suggest that traders pay less than $1 per $1,000 in par value for clearance, settlement, and other fixed costs.

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

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

[25] The age and time to maturity variables are transformed by the square root function to shrink large values since we do not expect that a 1-year difference in these variables has more effect when the values are low than high. We do not use the log transformation for this purpose because it expands low values too much.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Table V

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 (6) 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, as described in the text. Coefficient estimate t-statistics appear in parentheses.

	Coefficient Estimate					t-Statistic				
Representative Trade Size	10	20	100	200	1,000	10	20	100	200	1,000
Intercept (basis points)	−85.0	−79.0	−58.8	−47.6	−23.2	−37.6	−38.6	−39.9	−39.7	−29.7
Credit rating is BBB	4.4	3.4	4.2	4.6	3.1	7.0	5.7	8.2	10.2	10.3
Credit rating is B or BB	24.0	17.9	11.6	10.4	5.7	23.3	18.8	15.9	17.1	14.8
Credit rating is C and below	57.4	43.8	25.8	20.2	8.3	35.9	30.3	25.8	25.3	17.4
Coupon rate	1.5	1.1	0.3	0.1	0.1	8.1	6.4	2.2	1.5	3.7
Bond is in default	13.7	19.0	24.2	21.1	12.0	3.0	4.7	8.9	10.1	9.7
Years since issuance (sq. root)	5.8	5.7	4.4	4.3	3.5	16.1	16.9	15.9	18.3	22.7
Years to maturity (sq. root)	28.0	25.7	15.7	10.8	3.1	112.3	110.1	87.7	72.4	30.5
Bond is soon to be called	−73.5	−71.5	−44.8	−30.3	−18.7	−16.7	−15.8	−9.1	−7.0	−6.1
Bond has a sinking fund	−22.6	−19.3	−5.0	0.5	10.1	−4.1	−3.9	−1.6	0.2	7.6
Inverse average price (inverse percent of par)	7,508.9	7,107.8	5,317.4	4,251.0	2,098.4	44.0	47.1	53.8	55.3	41.1
Issue size (sq. root of millions)	−0.19	−0.27	−0.26	−0.22	−0.16	−5.5	−8.6	−11.7	−11.9	−13.7
Total other issues by same issuer (sq. root of millions)	0.06	0.06	0.07	0.06	0.01	19.3	22.0	30.6	28.1	7.2
Attached call	−8.8	−3.9	−0.9	−1.4	3.5	−11.4	−5.4	−1.5	−2.9	11.4
Attached put	−35.1	−36.7	−27.7	−19.0	−2.6	−12.0	−14.1	−15.3	−13.3	−2.7
Floating rate bond	−16.2	−15.2	−13.9	−13.7	−8.7	−8.5	−8.8	−10.6	−11.8	−9.0
Variable rate bond	11.6	11.2	8.7	5.3	0.6	6.3	6.6	6.5	4.8	0.9
Noncash call	1.5	1.2	−0.9	−1.4	0.0	0.7	0.6	−0.6	−1.2	0.0
Nonstandard accrual	3.5	3.9	2.4	1.5	1.7	2.7	3.2	2.8	2.0	3.7
Nonstandard payment	−0.1	0.4	2.6	6.2	7.2	−0.2	0.5	3.1	7.2	8.1
Maturity date extended or extendable	3.2	3.8	3.1	2.7	2.0	1.8	2.3	2.8	3.0	3.8
Issuer's equity is private	−4.8	−5.4	−3.9	−1.6	1.8	−4.3	−5.4	−5.8	−3.1	6.3
Rule 144a bond	−66.2	−58.3	−31.1	−18.8	−2.2	−35.6	−39.9	−37.7	−30.8	−6.1
Foreign bond	−9.5	−6.8	−1.3	−1.7	−2.0	−5.9	−4.7	−1.4	−2.3	−4.6
Global bond	−7.0	−7.3	−5.0	−3.0	0.1	−8.9	−10.2	−10.2	−7.6	0.3
Issuer is in finance industry	1.8	2.0	0.9	0.7	0.8	2.6	3.1	1.8	1.7	3.2
Issuer is a utility	−4.8	−4.9	−5.4	−4.8	−2.5	−5.2	−5.6	−8.7	−9.7	−8.1
TRACE-transparent (fraction of trades reported to public)	−5.4	−6.5	−5.1	−3.6	−2.5	−6.2	−8.0	−7.9	−6.5	−6.7
Issue listed on NYSE ABS	−11.4	−7.8	−1.5	−0.3	−0.3	−8.2	−6.1	−1.6	−0.4	−0.6
Adjusted R^2	52.8	52.6	45.3	40.0	27.5					
Sample size	21,965	21,965	21,965	21,965	21,965					

This content downloaded from 76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Large issues have significantly lower transaction costs than do small issues. The total size of other issues outstanding from the same issuer is a significantly positive determinant of transaction costs. This result is surprising 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 puts have significantly lower estimated transaction costs than those without such features. We find these results surprising since these features complicate bond valuation and Harris and Piwowar (2006) obtain different results in the municipal market. The call results may be explained by investors in the 2003 to 2005 period expecting many callable bonds to be called because yields had dropped significantly since these bonds were issued. Such bonds would behave more like short-term bonds than long-term bonds, and in turn would have lower transaction costs. Indeed, the results for the bonds identified in TRACE as soon-to-be-called are consistent with this explanation. The bonds that are most likely to be called are high coupon bonds. Accordingly, when the product of the 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).[26] Similarly, the put results may reflect the fact that the puts are expected to be exercised 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 fixed rate bonds, possibly because the variation in their coupons is correlated with variation in bond yields. Therefore, they 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 therefore may increase transaction costs. Except for the noncash calls, these results are 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.[27] Bonds issued by financial companies are slightly more expensive to trade. The private issuer results for small

[26] We do not include this product in the reported regressions because we feel that a proper analysis of this problem would require a full model of the probability that bonds would be called. We attempt to construct such a model, but find that our efforts are severely limited by the data available to us in the TRACE data set.

[27] "Rule 144a" refers to the rule titled "Rule 144a—Private Resales of Securities to Institutions" promulgated under the Securities Act of 1933, which allows Qualified Institutional Buyers to buy and trade unregistered securities.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

trade sizes are somewhat surprising since the values of these bonds are presumably harder to determine. However, Alexander et al. (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 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 other investors.

The result that bonds of foreign issuers have lower transaction costs than domestic issues is consistent with a separating equilibrium in which foreign companies access the U.S. capital markets (and agree to the disclosure requirements) to signal their quality (see Karolyi (2004)). The global bond results are more puzzling. The lower transaction costs could be related to cross-border competition or could proxy for another component of liquidity.

The final two regressors characterize the level of price transparency in TRACE or in the NYSE ABS. 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 for small trade sizes, 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 retail price information. We suspect that the TRACE effect would increase substantially if TRACE data were available more quickly and if they were available for more bonds during our sample period.

Almost all of the quantitative transparency results that we obtain from these regressions are larger in absolute value for smaller transaction sizes than for larger sizes. However, the relative transaction cost improvements are greater for the large trade sizes. Transaction costs for trades of 1,000 bonds in transparent bonds are about 25% less than similar-sized trades in opaque bonds; smaller transaction sizes experience cost improvements of only 7% to 10% in TRACE-transparent bonds. Therefore, institutions not only benefit from transparency, but on a relative basis they benefit more from transparency than retail customers even though retail customers experience larger absolute cost savings.

Overall, the cross-sectional results suggest that corporate bond transaction costs are negatively related to a bond's 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 (2006), although they find stronger results for the complexity measures.

The cross-sectional analyses also show that transparent bonds have lower transaction costs than do opaque bonds, after controlling for many other factors that affect transaction costs. Although our controls for other factors are quite comprehensive, it is always possible that some omitted variable or some nonlinearity in the population distribution may account for the results, in which case the residuals of the cross-sectional regression would be correlated and the significance of our results would be overstated. We address these potential

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

problems in the next section by analyzing changes in transaction costs around TRACE phase ins.

VI. Time-Varying Liquidity

The analyses above 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 each day for a class of bonds. We estimate the daily average transaction costs for bonds that became transparent in 2003, and compare these estimates to those for comparable bonds that were either TRACE-transparent throughout 2003 or never TRACE-transparent in 2003. We restrict our sample to 2003 for this analysis.

The regression model that we use to estimate daily transaction costs differs only in two respects from the time-series regression model that we use to estimate average transaction costs for a given bond. First, we specify separate average transaction cost functions, $c_T(S_t)$, 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:

$$c_T(S_t) = c_{0T} + c_{1T}\frac{1}{S_t} + c_{2T}\log S_t + \kappa_t. \tag{14}$$

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

$$\log V_t - \log V_s = f_s r_S + \sum_{J=S+1}^{T-1} r_J + f_t r_T + e_{st}, \tag{15}$$

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

$$\begin{aligned} r_{ts}^{P} &- Days_{ts}(5\% - CouponRate) \\ &= c_{0T}Q_t - c_{0S}Q_s + c_{1T}Q_t\frac{1}{S_t} - c_{1S}Q_s\frac{1}{S_s} + c_{2T}Q_t\log S_t - c_{2S}Q_s\log S_s \\ &\quad + f_s r_S + \sum_{J=S+1}^{T-1} r_J + f_t r_T + \eta_{ts} \end{aligned} \tag{16}$$

with the variance of η_{ts} given as before by, (8) above. Again, we estimate the model in stages using weighted least squares, where the weights are equal to the

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

predicted values of the regression of the squared residuals on the independent variables appearing in the residual variation expression.

Each of the 252 trading days in 2003 adds seven regression coefficients to the model, for a total of 1,764 parameters. To reduce the total estimation time, we estimate the model using a sliding window that is 3-months wide, and then we move forward 1 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 use estimates from the first and last regressions, respectively.

We compute transaction costs for various transaction sizes by evaluating the estimated transaction cost functions at the given 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 3, 2003.[28] These include all bonds rated A and above with original issues sizes greater than \$100 million and less than \$1 billion. This sample (T) includes 934,275 trades in 2,930 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. These bonds became transparent on July 1, 2002 because their original issue sizes are greater than \$1 billion. This sample includes 926,016 trades in 714 bonds. The second comparison sample (C2) includes all bonds rated A and above that were never TRACE-transparent during 2003.[29] The original issue sizes of these bonds were all less than \$100 million. This sample includes 460,913 trades in 6,121 bonds. The third comparison sample (C3) includes all BBB bonds with original issue sizes between \$100 million and \$1 billion that were never TRACE-transparent during 2003. This sample includes 997,324 trades in 2,625 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 therefore 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 3 bonds and those of each comparison group. We then separately regress these differences on a dummy variable that takes a value of 1 for dates on which prices in the T sample 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

[28] Results for the April 14, 2003 dissemination event are available from the authors upon request.

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

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Table VI

Time-Varying Transaction Costs Around the March 3, 2003 Event Date

Mean daily estimated transaction costs in 2003 by representative trade size (in basis points) before and after March 3 for bonds rated A and above that were made TRACE-transparent on March 3 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 $1 billion. 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. The third comparison sample consists of all BBB bonds with original issue sizes between $100 million and $1 billion 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 the 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 1 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 934,275, 926,016, 460,913, and 997,324 trades in 2,930, 714, 6,121, and 2,625 bonds. *** and * indicate that the transaction costs after March 3 are statistically different at the 1% and 10% levels from the transaction costs before March 3.

	Trade Size					
Sample	5	10	20	100	200	1,000
Mean estimates (basis points)						
T: Bonds rated A & above,	93.8	84.6	75.2	53.1	43.5	21.3
made transparent March 3 ($100M to 1B original issue size)	85.9***	77.0***	67.8***	45.9***	36.5***	14.6***
C1: Bonds rated A & above,	61.0	56.6	50.9	35.9	29.2	13.5
transparent throughout 2003 ($1B + original issue size)	57.0***	52.8***	47.4***	32.7***	26.2***	11.0***
C2: Bonds rated A & above,	105.5	96.3	87.1	65.9	56.7	35.2
never transparent in 2003 (<$100M original issue size)	114.3***	103.1***	92.3***	67.6	57.0	32.3*
C3: Bonds rated BBB, never	83.8	79.0	72.5	54.6	46.5	27.5
transparent in 2003 ($100M to 1B original issue size)	101.0***	96.1***	88.0***	64.1***	53.0***	26.9
Differences of differences						
T minus C1	−3.8	−3.8	−3.9	−4.1	−4.3	−4.0
	(−2.2)	(−2.4)	(−2.6)	(−2.6)	(−2.1)	(−3.9)
T minus C2	−15.9	−13.7	−12.1	−8.7	−7.5	−3.9
	(−6.2)	(−6.7)	(−6.7)	(−5.3)	(−3.5)	(−1.7)
T minus C3	−25.3	−24.8	−23.0	−16.8	−13.8	−6.0
	(−12.3)	(−13.6)	(−14.7)	(−13.4)	(−8.5)	(−5.6)
C1 minus C2	−12.1	−9.9	−8.1	−4.6	−3.1	0.3
	(−5.4)	(−5.7)	(−5.5)	(−3.8)	(−2.2)	(0.2)
C2 minus C3	−9.4	−11.0	−10.9	−7.9	−6.3	−2.2
	(−4.8)	(−7.3)	(−7.9)	(−7.0)	(−5.4)	(−1.2)

The *t*-statistics for the differences of differences appear in parentheses.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

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,[30] and assume that the variance of the latter component is constant. We estimate the resulting model using maximum likelihood methods.

The results in Table VI suggest that transparency significantly decreases transaction costs. Transaction costs decrease in comparison to each of the three comparison samples. The decrease is generally greater for smaller trade sizes, most probably because larger traders already have substantial knowledge of bond values, and hence lower initial transaction costs.

The decrease in transaction costs is greater when measured relative to the bonds that were not 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) fall relative to 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 are correlated with original issue size. However, note that little average difference exists between the two controls samples (C2 and C3), for which prices are never transparent despite their cross-sectional differences: C2 consists of small bond issues rated A and above while C3 consists of intermediate-sized BBB issues.

VII. Conclusion

Corporations raise substantial financing in the bond markets. A better understanding of the liquidity of these markets 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. Thus, 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 1.24% of the price of representative retail-sized trades ($20,000). This is the equivalent of over 2 months of the total annual return for a bond with a 6% yield to maturity, or 52 cents per share for a $40 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.

Corporate bond transaction costs are much lower for institutional-sized transactions. Because other studies notice this pattern in traditional dealer markets, we can assume that the bond markets might benefit from some of the market-driven technological innovations experienced in other dealer markets.

[30] 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.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

The new transparency may increase the technological progress of the corporate bond market.

The strongest arguments against transparency involve concerns about an increase in the difficulty of dealers to manage inventory, especially in higher credit risk bonds. However, the management of inventory problems is easier in the debt markets than in the equity markets, both 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 the relatively more transparent equity markets and our empirical results, we believe that it would be extremely unlikely that increased bond market transparency would lower liquidity.

Indeed, additional transparency is likely to encourage the creation of more efficient market structures and innovative dealing strategies that can further reduce transaction costs. If so, the benefits of transparency estimated in this paper can be expected to be far smaller than their full benefits.

REFERENCES

Alexander, Gordon, Amy Edwards, and Michael Ferri, 2000, The determinants of trading volume of high-yield corporate bonds, *Journal of Financial Markets* 3, 177–204.

Amihud, Yakov, and Haim Mendelson, 1991, Liquidity, maturity, and yields on U.S. Treasury securities, *Journal of Finance* 46, 1411–1425.

Barclay, Michael, Terrence Hendershott, and Kenneth Kotz, 2006, Automation versus intermediation: Evidence from Treasuries going off the run, *Journal of Finance* 61, 2395–2414.

Bernhardt, Dan, Vladimir Dvoracek, Eric Hughson, and Ingrid Werner, 2005, Why do larger orders receive discounts on the London Stock Exchange? *Review of Financial Studies* 18, 1343–1368.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2006, Optimal market transparency: Evidence from the initiation of trade reporting in corporate bonds, *Journal of Financial Economics* 82, 251–288.

Biais, Bruno, Larry Glosten, and Chester Spatt, 2005, Market microstructure: A survey of microfoundations, empirical results, and policy implications, *Journal of Financial Markets* 8, 217–264.

Biais, Bruno, and Richard Green, 2005, The microstructure of the bond market in the 20th century, Working paper, Carnegie Mellon University.

Blume, Marshall, Donald Keim, and Sandeep Patel, 1991, Returns and volatility of low-grade bonds, *Journal of Finance* 46, 49–74.

Chakravarty, Sugato, and Asani Sarkar, 2003, Trading costs in three U.S. bond markets, *Journal of Fixed Income* 13, 39–48.

Cornell, Bradford, and Kevin Green, 1991, The investment performance of low-grade bond funds, *Journal of Finance* 46, 29–48.

Fenn, George, 2000, Speed of issuance and the adequacy of disclosure in the 144a high-yield debt market, *Journal of Financial Economics* 56, 383–405.

Goldstein, Michael, Edith Hotchkiss, and Erik Sirri, 2006, Transparency and liquidity: A controlled experiment on corporate bonds, *Review of Financial Studies* (forthcoming).

Green, Richard, Burton Hollifield, and Norman Schürhoff, 2004, Financial intermediation and the costs of trading in an opaque market, Working paper, Carnegie Mellon University.

Harris, Lawrence, and Michael Piwowar, 2006, Secondary trading costs in the municipal bond market, *Journal of Finance* 61, 1361–1397.

Hong, Gwangheon, and Arthur Warga, 2000, An empirical study of bond market transactions, *Financial Analysts Journal* 56, 32–46.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms

Hotchkiss, Edith, and Tavy Ronen, 2002, The informational efficiency of the corporate bond market: An intraday analysis, *Review of Financial Studies* 15, 1325–1354.

Hotchkiss, Edith, Arthur Warga, and Gergana Jostova, 2002, Determinants of corporate bond trading: A comprehensive analysis, Working paper, Boston College.

Kalimipalli, Madhu, and Arthur Warga, 2002, Bid/ask spread, volatility and volume in the corporate bond market, *Journal of Fixed Income* 12, 31–42.

Karolyi, G. Andrew, 2004, The world of cross-listings and cross-listings of the world: Challenging conventional wisdom, Working paper, Ohio State University.

Madhavan, Ananth, 2000, Market microstructure: A survey, *Journal of Financial Markets* 3, 205–208.

O'Hara, Maureen, 1997, *Market Microstructure Theory* (Basil Blackwell, Cambridge, MA).

Reiss, Peter, and Ingrid Werner, 1996, Transaction costs in dealer markets: Evidence from the London Stock Exchange, in Andrew Lo, ed.: *The Industrial Organization and Regulation of the Securities Industry* (University of Chicago Press, Chicago, IL).

Sarig, Oded, and Arthur Warga, 1989, Bond price data and bond market liquidity, *Journal of Financial and Quantitative Analysis* 24, 367–378.

Schultz, Paul, 2001, Corporate bond trading costs: A peek behind the curtain, *Journal of Finance* 56, 677–698.

Warga, Arthur, 1992, Bond returns, liquidity and missing data, *Journal of Financial and Quantitative Analysis* 27, 605–616.

This content downloaded from
76.36.240.129 on Wed, 31 Jan 2024 18:23:40 +00:00
All use subject to https://about.jstor.org/terms