INFORMED TRADING AND ITS IMPLICATIONS FOR COPORATE BOND PRICING

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Valuation of corporate debt has been an extremely important, albeit imprecise task in asset pricing. Both structural models and reduced form models have had limited success in explaining the corporate yield spreads observed in actual markets. Taking advantage of a unique corporate bond dataset from the National Association of Securities Dealers, this dissertation investigates whether informed trading takes place in the high-yield corporate bond market, and its implications for corporate bond pricing. Differing from previous studies, I find that current corporate bond returns have explanatory power for future stock price changes. This implies that the corporate bond market serve important roles in disseminating new information. Based on this finding, this dissertation also demonstrates that in addition to liquidity, the amount of information based trading plays an important role in determining yield spreads of risky corporate bonds, which is consistent with the hypothesis that investors require higher return to compensate them for bearing the risks of trading with more informed traders. In line with a strand of recent literature on the implications of market microstructure for asset pricing, this paper suggests that corporate bond yields might embed an information risk premium that is ignored by existing bond pricing models.

BIOGRAPHICAL SKETCH

Xing Zhou was a Ph.D. student in the department of Applied Economics and Management at Cornell University from the 2001 to 2006. He defended this dissertation in the August of 2006, and then became a faculty member at the Rutgers Business School in Rutgers University-The State University of New Jersey.

Prior to entering Cornell for his Ph.D. degree, Xing received his Bachelor of Arts degree from Peking University in China in 2000, and his Master of Science degree from the Ohio State University in 2001.

TO MY PARENTS

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CHAPTER 1

INFORMATION-BASED TRADING IN THE JUNK BOND MARKET

Introduction

Since 1934, when the United States Congress enacted the Securities Exchange Act, the stock and the options markets have been under intense scrutiny for potential abuse of material nonpublic information. However, information-based trading also seems to be taking place in the corporate bond market, as investigations by the Securities and Exchange Commission (SEC) and the U.S. Attorney's Office have revealed the occurrence of insider trading and price manipulation in the junk bond[1] market by the "king of junk bonds"— Michael Milken. In 1989, James Dahl, an employee of Milken's junk bond department, swore before a grand jury that Milken advised him to buy up Caesar's World bonds from their own customers on the day when Milken made a presentation to Caesar's World on how to handle their finance, i.e., a sales pitch. In 1990, Michael Milken pleaded guilty to six felony counts in connection with insider trading, and he was sentenced by federal Judge Kimba Wood to 10 years in prison (though he was released in 1993).

Michael Milken is not the only one who acted inappropriately on private information in the once arcane world of high-yield debt market. Institutional investors and investment bankers who trade high-yield corporate bonds every so often participate in syndicated loans for the same company issuing high-yield bonds. Since investors who lend to the company are entitled to send representatives to regular

[1] A bond rated BB or lower because of its high default risk. Also known as a high-yield bond, or speculative bond.

meetings with the borrowing company's management and bankers, they obtain access to some confidential information, such as updated projections of revenues and earnings, or plans for an acquisition or divestiture, which public investors will never see. When such information from internal discussions is improperly leaked or misused, prices of the borrowing company's bonds will be affected and investors acting on this private information will make profits. Indeed, trading based on such private information in the credit markets has been warned about in research work authored by Chris Dialynas, a managing director and portfolio manager at Pacific Investment Management Co., which is one of the world's top bond investors. Furthermore, former SEC chairman Arthur Levitt stated that the SEC has "found anecdotal evidence of the possible misuse of inside information in the high-yield (debt) market[2]".

At a first glance, it is counter-intuitive that investors with private information about a company will trade in its debt securities. Even though the value of a company's debt, equity and its derivatives will all be affected by information related to the issuing company's underlying assets, investors who posses such undisclosed information will presumably trade in the equity security and/or its derivatives, rather than in the debt securities. According to a recent study released by the SEC [Edwards, Harris and Piwowar (2004)], average transaction costs for trades in corporate bonds are higher than in stocks. Furthermore, unlike options, corporate bonds do not provide higher leverage than stocks. If trading corporate bonds incurs higher transaction costs but offers lower leverage, why would an informed investor trade in the corporate bond market?

[2] See speech by SEC Chairman Arthur Levitt: "The Importance of Transparency in America's Debt Market", at the Media Studies Center, New York, N.Y., on September 9th, 1998.

Several explanations stand out when we look into the transaction costs argument and the market structure for high-yield corporate bonds. First of all, as it has been documented in several previous studies, the value of high-yield corporate debt is very sensitive to firm-specific information, especially extreme information regarding the state of the company. Therefore, the high-yield corporate bond market offers potential profitable opportunities for trading on nonpublic information. More importantly, these opportunities provide an additional venue for an informed trader to strategically exploit his private information. Conventionally, an informed trader employs optimal trading strategies in the stock and the options markets to make the most out of his information. These trading strategies typically include certain trading intensity over multiple trading periods, as well as an optimal order size for each individual period [see for example, Kyle (1984, 1985), Foster and Viswannathan (1993) and Holden and Subrahmanyam (1992)]. Conceivably, trading too aggressively on the private information in stocks and options makes it harder for the informed trader to hide from the marker maker and the regulators, and hence increases his transaction costs. As the informed trader becomes more aggressive, trading in stocks and options gets more and more expensive. At some point, the marginal cost from trading an additional amount of stocks and options exceed that for a first trade in high-yield bonds. As a result, substituting a certain amount of excess trading in stocks and options with a trade in the issuer's high-yield debt might better serve the informed trader's goal in maximizing his total profits. Furthermore, given the fact that the debt securities market has been subject to much less scrutiny for insider trading compared to the markets for equity securities and derivative securities, informed traders have much lower perceived probability of being detected and prosecuted. Datta and Datta argue that "the absence of any reporting requirement for insider bond transactions may create an enhanced opportunity for insiders to exploit private information to expropriate wealth from uninformed bond traders." Consequently, to take full advantage of his private information, the informed trader will choose to trade a certain amount of high-yield bonds, in addition to some quantity of stocks and options of the issuer.

In addition to higher transaction costs from more aggressive trading in stocks and options, there are other important factors that play a role in encouraging an informed trader to trade in the junk bond market. These factors include some common practices within the bond industry, and the trader's degree of risk aversion. First, differing from the equity market, the high-yield corporate debt market is largely institutional. Institutional investors who trade high-yield corporate bonds sometimes buy syndicated loans for the same company issuing high-yield bonds. In addition, these investors in syndicated loans are often also traders, who trade bank loans next to high-yield bonds. In fact, it is quite often that a single trader at a hedge fund deals in all of a company's debt instruments. Under such porous circumstances, keeping private information private and avoiding improper use of this information is a challenge. "You can't put a Chinese wall through someone's head," says Michael Kaplan, a partner in the corporate practice at law firm Davis Polk & Wardwell[3].

Second, for some risk averse investors, even if they have access to some information about a pending large change in the firm's asset value, they might choose to trade in bonds to stay away from down-side risk, as their aversion to risk cannot be fully eliminated by the piece of information they have, especially when they are not so

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[3] For further discussion of insider trading in the bond market, see a recent article by Carolyn Sargent: "The New Insider Trading?" Investment Dealers' Digest, October 31st, 2005.

sure about the quality of the information. While it is true that the down-side risk can be easily hedged in the options market, associated transaction costs might render direct trading in bonds a better choice.

If an informed trader trades corporate bonds as well as stocks and options, new information will be disseminated in all three related markets. Thus, current bond prices hypothetically contain valuable information about future price movements in the stock and options markets. Taking advantage of a unique corporate bond transaction dataset for a set of 50 most frequently traded high-yield corporate bonds from NASD, this paper empirically tests this hypothesis and explores the dynamics of information flow across related markets by examining the pair-wise lead-lag relations between stocks, corporate bonds and options. Differing from previous studies, I find that current high-yield corporate bond price changes have explanatory power for future stock returns. This implies that the bond market serves an important role in disseminating new information. The option market, however, contains valuable information about future movements in both the stock and the bond market, and these relations are unidirectional, suggesting that the option market is a preferred venue for informed trading. Furthermore, there is strong evidence that informed trading in the option market is distributed across different strike prices, with at-the-money options attracting investors who posses mild firm-specific information, and deep out-of-the-money options catching the attention of those who obtain extreme information.

The rest of the paper is organized as follows. Section 2 summarizes some recent developments in the corporate bond over-the-counter (OTC) market and the new Trade Reporting and Compliance Engine (TRACE) introduced by NASD. The stock, bond and options data are described in Section 3. Section 4 investigates pairwise lead-lag relationships between stocks, bonds and options. Whether these relationships are subject to infrequent trading in bonds and how they vary with firm size are addressed in Section 5. Section 6 concludes and points out some possible extensions.

The Corporate Bond Market and NASD's TRACE

The corporate bond market assumes roughly as important a role in corporate financing as the equity market, with approximately $4.4 trillion outstanding in 2004, which is larger than both the US treasury market ($3.8 trillion outstanding) and the municipal bond market ($2.0 trillion outstanding)[4]. The stock market is larger at about $15 trillion[5]. The total dollar volume of the bond market in 2003 is about $10 trillion, more than the trading volume on the NYSE[6]. About $18 billion in par value of corporate bonds turns over in roughly 22,000 transactions on a typical day[7]. As baby-boomers age and shift more of their assets from equity investments to debt investments, the corporate bond market will certainly grow in both size and importance.

However, transparency in this market has never been comparable to that of other securities markets. As Doug Shulman (NASD's President of Markets) said, the corporate bond market 'has been largely a mystery to retail investors'. Following insider trading and price manipulation scandals in the corporate bond market in the late 1980's, the opaqueness of the corporate fixed-income market, especially that of

4 NASD News Release, March 26th, 2004.
5 Business Times, Feb 8th, 2005
6 The Economist, Oct 14th, 2004
7 See a speech by Doug Shulman, NASD's President of Markets, on February 2nd, 2005 in New York, New York, 'Bond Market Association Legal and Compliance Conference Keynote Address', which is on the NASD's website.

the high-yield bond market, became a really big concern for the U.S. Congress and the SEC. The Fixed Income Pricing System (FIPS) was the result of discussions between the SEC and the NASD on how to increase the transparency of the junk bond market. FIPS helps regulators effectively monitor trading in high-yield debt. On April 11th, 1994, The Nasdaq Stock Market, Inc., began operation of FIPS for members trading high-yield bonds. Under the FIPS system, NASD members are required to report all secondary market transactions on a selected set of high-yield bonds within 5 minutes of execution. Based on submitted transaction reports, hourly price and volume data on about 50 most frequently traded high-yield bonds are displayed on the FIPS terminal. Even though FIPS brought some transparency to the high-yield debt market, the corporate debt market as a whole still does not live up to regulators' expectation of a transparent market. In 1998, former SEC Chairman Levitt noted that "[t]he sad truth is that investors in the corporate bond market do not enjoy the same access to information as a car buyer or a homebuyer or, dare I say, a fruit buyer." In order to further increase the transparency of the corporate bond markets, NASD initiated a broader system know as TRACE (Trade Reporting and Compliance Engine) on July 1st, 2002, which incorporated the previous FIPS system. Under TRACE rules[8] , all NASD members were obligated to submit transaction reports for any secondary market transaction in TRACE-eligible securities[9] between 8:00PM and 6:30PM (EST) within one hour and fifteen minutes of the time of execution[10]. Transaction

8 Also known as the NASD Rule 6200 Series.

9 According to NASD Rule 6210(a), TRACE-eligible security 'mean all United States dollar denominated debt securities that are depository eligible securities under Rule 11310(d); Investment Grade or Non-Investment Grade; issued by United States and/or foreign private issuers; and: (1) registered under the Securities Act of 1933 and purchased or sold pursuant to Rule 144A of the Securities Act of 1933.' It does not include debt securities issued by government-sponsored entities (GSE), mortgage-backed or asset-backed securities, collateralized mortgage obligations and money market instruments.

10 For a detailed description of TRACE rules and their subsequent amendments, please refer to NASD Notice to Members NtM-02-76, NtM-03-12, NtM-03-22, NtM-03-36, NtM-03-45, NtM-04-39 and NtM-04-65.

information on TRACE-eligible securities which are investment grade[11] and have an initial issuance of $1 billion or higher is subject to immediate dissemination. Additionally, 50 Non-Investment grade and most actively traded TRACE-eligible securities (TRACE 50 thereafter) are designated for dissemination. In the subsequent two and half years, major improvements to the TRACE system have focused on increasing dissemination and reducing reporting time. As of July 1st, 2002, only 540 securities are subject to dissemination. This number went up to 4,500 after NASD began distributing information on a third group of Investment Grade TRACE-eligible securities that are rated ‘A3’ or higher by Moody’s or ‘A-’ or higher by S&P and have a $100 million or higher original issue size on March 3rd, 2003, and another group of 120’Baa/BBB’ rated bonds on April 14th, 2003. After another two-stage implementation of the amendments to the TRACE Rules, which were approved by SEC on September 3rd, 2004, NASD started full dissemination of transaction information on all TRACE-eligible securities except those Section 4(2)/Rule 144A TRACE-eligible securities. Currently about 29,000 corporate bonds, another jump from 17,000 as of October 1st, 2004, have their transaction and price data spread to the market in real-time, and the corporate bond markets have never before been so transparent. Meanwhile, the time to report a trade of a Trace-eligible security has been declining. Starting from 75 minutes on July 1st, 2002, the reporting period went down to 45 minutes on October 1st, 2003 and further down to 30 minutes on October 1st, 2004. It was shortened to just 15 minutes on July 1st, 2005.

TRACE improves on FIPS in several important ways. First, FIPS only covered non-convertible, non-investment grade and publicly offered debt which is not

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11 Rated by a nationally recognized statistical rating organization (NRSRO) in one of its four highest generic rating categories. See NASD Rule 6210(h).

part of a medium-term note program[12], and only a set of 50 most actively traded bonds were subject to dissemination. However, under TRACE rules, transaction information for any secondary market transaction in all TRAC-eligible securities are required to be reported to NASD, and starting February 7th, 2005, NASD has begun to fully disseminate transaction information on the entire universe of corporate bonds, which is considered by NASD as the most significant innovation for retail bond investors in decades. Second, for each debt security that is subject to dissemination, TRACE dramatically increase the amount of information distributed to the public. FIPS only published hourly summaries on the prices and total volume of transaction in a set of 50 bonds, while transaction and price data on each trade in TRACE-eligible securities are distributed to the market.

Data

The transaction dataset for TRACE 50 high-yield bonds contains execution date and time (recorded to the second), price, yield, quantity, and some other information that can be used to purge invalid transaction reports for every trade from July 1st, 2002 to September 30th, 2004[13]. The TRACE 50 bonds are chosen by the NASD advisory committee based on criteria such as the security's volume, price, name recognition, amount of research attracted, a minimum amount of bonds outstanding, number of dealers that are making a market in this security and the security's contribution to the TRACE 50's industry diversity. Similar to FIPS 50, the TRACE 50 are characterized by high trading volume, both in terms of number of transactions and number of block size trades, and similar trading patterns to the

12 Nasdaq Stock Market, Inc., 1997, Rule 6210(i).

13 On October 1st, 2004, NASD started its second stage dissemination, and many more high-yield bonds are subject to dissemination. The concept of TRACE 50 does not exist any more.

issuer's stock. Over time, bonds with small trading volume were replaced with more active bonds. Transaction information on the first TRACE 50 bonds was released to the market on real-time basis for about one year since July 1st, 2002. Beginning on July 13th, 2003, the TRACE 50 list was updated every 3 month until September 30th, 2004. During this time period (July 1st, 2002 to September 30th, 2004), 177 high-yield bonds from 135 issuing firms were included in the TRACE 50 lists for dissemination.

Daily closing stock price and related options quotes data for the issuing firms are obtained from OptionMetrics INC for the period from July 1st, 2002 to April 15th, 2004. Only 129 bonds from 110 firms are subject to dissemination during this period. Since some companies are not public, and some are traded on the OTC market or the pink sheet market, stock price data do not exist for 18 of these firms. This reduces the sample to 92 firms. Furthermore, 15 out of the 92 firms do not have options traded on their common stock during this period. By excluding these 15 firms from my sample, I was left with 77 firms with 111 bonds.

To avoid potential bias from non-synchronous trading, a daily time series dataset is formed by keeping the transaction price for the last valid trade before 4:00PM (EST) for each of these 111 bonds. As several firms have multiple bonds included in TRACE 50 list during certain periods of time, only the most active bond with the highest priority in payments is kept for inter-market analysis[14]. As a result, a panel of daily stock, bond and options data for 77 firms is employed for this study.

Table 1 contains summary characteristics for the 77 corporate bonds and their

14 Examining the price behavior of different bonds issued by the same firm is another interesting topic for future research.

issuing firms at the time of their initial entry to the TRACE 50 list. Issuing firms are fairly large with median total asset value of 11471.1 million USD and characterized by high financial leverage, which is consistent with low credit ratings of these bonds. Also consistent with the high-yield nature, many bonds in the sample contain embedded options. Of the 77 bonds, 38 (49.35%) are callable prior to maturity and 14 (18.18%) are convertible. The bonds included in this study represent 7 different industries and they are concentrated in Manufacturing (38.96%), Servicing (31.17%) and Energy (11.69%). About half of the 77 bonds are senior unsecured notes. Senior notes and subordinated notes account for another 30 percent of the sample. Coupon payments are made twice per year for each of the 77 bonds, and all are fixed plain vanilla coupons, except for one bond which has a variable coupon size. The average coupon rate is 7.48%. About 80% of the TRACE 50 bonds are rated no lower than B- by S&P and none of them defaulted during the sample period.

The use of option quotes data, instead of transaction data, deserves some comments. Information-based market microstructure models demonstrate that the bid-ask spread reflects a balancing of losses to the informed traders with gains from the uninformed traders and therefore contains information about the probability of trading on private information in the market [See Copeland and Galai (1983), Glosten and Milgrom (1985) and Easley and O'Hara (1987, 1992)]. In addition, as shown by Chan, Chung and Fong (2002), because of generally larger bid-ask spread in the option market, as documented by Vijh (1999), informed traders might have an incentive to submit limit orders instead of market orders, and hence quote revisions contain valuable information about future market movements. Moreover, since corporate bonds embed a short position in puts on the value of the firm, call option data are eliminated from the sample. Finally, as will be shown in the next section,

Table 1.1: Characteristics of 77 TRACE 50 Bonds and Their Issuing Firm

Panel A:

Variable	Mean	Median	Minimum	Maximum	Std Dev
Assets	11471.1	8394	523.8	63545	10195.2
Leverage	0.7819	0.7773	0.3586	1.9119	0.2128
Coupon Rate	7.4812	7.875	1.25	11	2.2228
Time to Maturity	6.369	5.8344	2.0862	26.705	3.3646

Panel B:

Bond Type	*SRDEB*	*SRNT*	*SRSECNT*	*SRSUBNT*
Number of Bonds	1	12	2	8
Percentage	1.32	15.79	2.63	10.53
Bond Type	SRUNNT	SUBDEB	SUBNT	UNNT
Number of Bonds	38	1	10	4
Percentage	50	1.32	13.16	5.26

Panel C:

S&P Rating	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*NR*
Number of Bonds	7	24	29	7	1	1	7
Percentage	9.21	31.58	38.16	9.21	1.32	1.32	9.21

Panel D:

Coupon Type	*Variable*	*Plain Vanilla Fixed Coupon*
Number of Bonds	1	76
Percentage	1.3	98.7

Panel E:

Payment Frequency	*Semiannually*
Number of Bonds	77
Percentage	100

Panel F:

Industry	*CG*	*ENGY*	*FIN*	*MANU*	*SERV*	*TELE*	*TRANS*
Number of Bonds	1	9	7	30	24	5	1
Percentage	1.3	11.69	9.09	38.96	31.17	6.49	1.3

Panel G:

Callable	*Yes*	*No*
Number of Bonds	38	39
Percentage	49.35	50.65

Table 1.1 (Continued)

Panel H:

Convertible	*Yes*	*No*
Number of Bonds	14	63
Percentage	18.18	81.82

This table contains summary characteristics for the 77 corporate bonds and their issuing firms at the time of their initial entry to the TRACE 50 list. Firm characteristics are based on data from COMPUSTAT, while bond characteristics are determined from the TRACE 50 dataset. Most of these descriptive bond data were obtained from NASD, with the remainder provided by the issuing firms. The following abbreviations are used in this table: for bond type, SRDEB (Senior Debenture), SRNT (Senior Note), SRSECNT (Senior Secured Note), SRSUBNT (Senior Subordinated Note), SRUNNT (Senior Unsecured Note), SUBDEB (Subordinated Debenture), SUBNT (Subordinated Note) and UNNT (Unsecured Note); for industry, CG (Consumer Goods), ENGY (Energy), FIN (Financial), MANU (Manufacturing), SERV (Services), TELE (Telecommunications) and TRANS (Transportation).

ATM options and OTM options carry different information about future movements in stocks and bonds. Therefore, both ATM and deep OTM put option spreads are kept for each firm.

Inter-Market Relationships between Stocks, Bonds and Options

If new information about the value of an individual firm exists in the market, it should be reflected in the prices of the firm's stock and options, as well as its bonds. This section provides a comprehensive examination of pair-wise relationships between stocks, bonds and options. Daily stock returns, $SR_{i,t}$, and daily bond returns, $BR_{i,t}$, are calculated using the end-of-day closing prices. For the options market, normalized spreads for both ATM and deep OTM puts are calculated by dividing the bid-ask spread by the midpoint of bid and ask quotes. These are denoted as $AS_{i,t}$ and $OS_{i,t}$ respectively.

In order to isolate interest rate risk, for each individual corporate bond I construct a corresponding default-free bond whose future cash flows match those of the corporate bond perfectly. The price of default-free bonds can simply be calculated by discounting the cash flows at corresponding default-free zero-coupon interest rates. These zero-coupon rates are estimated by employing a modified version of the extended Nelson-Siegel model [Bliss (1997)] on the observed on-the-run Treasury curve[15]:

(1.1) $\min_{\beta_0,\beta_1,\beta_2,\tau_1,\tau_2} \sum_{i=1}^{N_t} (w_i \varepsilon_i)^2,$

subject to

(1.2) $r(m_{\min}) \geq 0,$

(1.3) $r(m_{\max}) \geq 0,$

and

(1.4) $\exp[-r(m_k)m_k] \geq \exp[-r(m_{k+1})m_{k+1}],\ \forall m_{\min} \leq m_k < m_{\max},$

where

(1.5) $w_i = \frac{1/d_i}{\sum_{j=1}^{N_t} 1/d_j},$

(1.6) $r(m) = \beta_0 + \beta_1\left[\frac{1-e^{-m/\tau_1}}{m/\tau_1}\right] + \beta_2\left[\frac{1-e^{-m/\tau_2}}{m/\tau_2} - e^{-m/\tau_2}\right],$

15 Hotchkiss and Ronen (2002) calculate these default-free zero-coupon rates by using a method proposed by Fisher, Nychka, and Zervos (1994). However, based on a series of parametric and nonparametric tests, Bliss (1997) compares five distinct term structure estimation methods, including the smoothed and unsmoothed Fama-Bliss methods, the McCulloch model, the Fisher-Nychka-Zervos method and the extended Nelson-Siegel model, and concludes that the Fisher-Nychka-Zervos method does almost always poorly relative to the other four alternatives, in terms of both in-sample goodness-of-fit and out-of-sample performance.

(1.7) $\hat{p}_i = \sum c_{i,m} e^{-r(m)m}$,

and

(1.8) $\varepsilon_i = p_i - \hat{p}_i$.

In this model, m represents time to maturity, $r(m)$ is the discount rate for coupon or principal payments at time m, d denote Macaulay duration, and c refers to cash flows. Based on the prices of the constructed default-free bonds, their returns, $DR_{i,t}$, can be readily calculated. Furthermore, to control for the effect of market-wide information, I include the S&P 500 index return, denoted as MR_t, in the model. Data for both the observed on-the-run Treasury curve and the S&P 500 index return are retrieved from the Center for Research in Security Prices (CRSP).

The Empirical Model

To examine whether information-based trading takes place in the corporate bond market, the following panel Vector Auto-Regression (VAR) model with two controlling variables is estimated. Based on this model, Granger causality tests are conducted to identify pairwise lead-lag relationships between stocks, bonds and options:

(1.9) $Y_{i,t} = \mathrm{A} + \sum_{j=1}^{J} B_{-j} Y_{i,t-j} + C_t X_t + E_{i,t}$,

where

(1.10) $Y_{i,t} = [SR_{i,t}, BR_{i,t}, AS_{i,t}, OS_{i,t}]'$,

(1.11) $X_t = [MR_t, DR_t]'$,

(1.12) $A = [\alpha_1, \alpha_2, \alpha_3, \alpha_4]'$,

(1.13) $B_{-j} = \begin{bmatrix} \beta_{11,-j} & \beta_{12,-j} & \beta_{13,-j} & \beta_{14,-j} \\ \beta_{21,-j} & \beta_{22,-j} & \beta_{23,-j} & \beta_{24,-j} \\ \beta_{31,-j} & \beta_{32,-j} & \beta_{33,-j} & \beta_{34,-j} \\ \beta_{41,-j} & \beta_{42-j,} & \beta_{43-j,} & \beta_{44,-j} \end{bmatrix}$,

(1.14) $C = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \\ \gamma_{41} & \gamma_{42} \end{bmatrix}$

and

$$(1.15)\ E_{i,t} = [\varepsilon_{i1,t} \quad \varepsilon_{i2,t} \quad \varepsilon_{i3,t} \quad \varepsilon_{i4,t}]'.$$

A, B and C contain parameters to be estimated, and E_t is the error vector. This model is estimated by generalized least squares (GLS) with error terms corrected for auto-correlation.

As individual corporate bonds tend to be less frequently traded than their corresponding stocks and options, even for TRACE 50 which are considered more active than other high-yield bonds [Hotchkiss and Nolen (2002)], this model is first estimated with data on 48 firms with relatively high bond volume to mitigate potential bias introduced by infrequent trading. Table 2 contains summary statistics about characteristics of the 48 bonds and their issuing firms.

Table 1.2: Characteristics of 48 Most Frequently Traded TRACE 50 Bonds and Their Issuing Firms

Panel A:

Variable	Mean	Median	Minimum	Maximum	Std Dev
Assets	14259.7	10709.7	1613	63545	11564.6
Leverage	0.7963	0.7843	0.4444	1.5206	0.1946
Coupon Rate	7.4121	7.75	1.25	11	2.247
Time to Maturity	6.721	5.8344	2.0862	26.705	4.0662

Panel B:

Bond Type	*SRDEB*	*SRNT*	*SRSECNT*	*SRSUBNT*	*SRUNNT*	*SUBNT*	*UNNT*
Number of Bonds	1	7	2	4	24	7	3
Percentage	2.08	14.58	4.17	8.33	50.00	14.58	6.25

Panel C:

S&P Rating	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*NR*
Number of Bonds	4	16	17	5	1	0	5
Percentage	8.33	33.33	35.42	10.41	2.08	0.00	10.42

Table 1.2 (Continued)

Panel D:

Coupon Type	*Variable*	*Plain Vanilla Fixed Coupon*
Number of Bonds	1	47
Percentage	2.08	97.92

Panel E:

Payment Frequency	*Semiannually*
Number of Bonds	48
Percentage	100.00

Panel F:

Industry	*CG*	*ENGY*	*FIN*	*MANU*	*SERV*	*TELE*	*TRANS*
Number of Bonds	1	7	4	16	15	5	0
Percentage	2.08	14.58	8.33	33.33	31.25	10.42	0.00

Panel G:

Callable	*Yes*	*No*
Number of Bonds	23	25
Percentage	47.92	52.08

Panel H:

Convertible	*Yes*	*No*
Number of Bonds	12	36
Percentage	25.00	75.00

This table contains summary characteristics for the 48 most frequently traded TRACE 50 bonds and their issuing firms at the time of their initial entry to the TRACE 50 list. Firm characteristics are based on data from COMPUSTAT, while bond characteristics are determined from the TRACE 50 dataset. Most of these descriptive bond data were obtained from NASD, with the remainder provided by the issuing firms. The following abbreviations are used in this table: for bond type, SRDEB (Senior Debenture), SRNT (Senior Note), SRSECNT (Senior Secured Note), SRSUBNT (Senior Subordinated Note), SRUNNT (Senior Unsecured Note), SUBDEB (Subordinated Debenture), SUBNT (Subordinated Note) and UNNT (Unsecured Note); for industry, CG (Consumer Goods), ENGY (Energy), FIN (Financial), MANU

(Manufacturing), SERV (Services), TELE (Telecommunications) and TRANS (Transportation).

Bond-stock relationships

According to the structural firm-value approach to the valuation of corporate debt (Merton (1974)), corporate bonds can be viewed as risk-free debt combined with a short position in a put on the value of the firm's assets. Since equity can be considered a call option on the assets, if financial markets are efficient, stock and bond prices should move simultaneously with no lead-lag relationship, and the direction of contemporaneous movements should reveal the nature of information in the markets: information about the mean value of the issuing firm's assets leads to positive correlation between stock and bond returns, while information related to changes in the volatility of the firm's asset returns causes negative correlation.

Due to the lack of adequate corporate bond data, few studies have empirically examined the stock-bond relationship. Early research on the stock-bond linkages has been conducted on the aggregate level, looking at low-grade bonds [Blume, Keim and Patel (1991), Cornell and Green (1991)]. While both Cornell and Green (1991) and Blume, Keim and Patel (1991) find that speculative bonds are very sensitive to stock price movements, neither study is able to identify a significant impact of previous or future stock returns on current corporate bond returns. As the corporate bond market has become more transparent, two studies in the literature have explicitly examined the lead-lag relationship on the individual firm level. However, their results are contradictory. Using weekly quotes data from Merrill Lynch, Kwan (1996) finds that lagged stock returns have explanatory power for current bond yield changes, but not vice versa. Based on this finding, he concludes that ‘stocks lead bonds in reflecting firm-specific information’. In contrast, Hotchkiss and Ronen (2002) analyze a transaction dataset for 55 high-yield bonds included on the NASD Fixed Income Pricing System (FIPS)[16] and reject the hypothesis that stocks lead bonds in reflecting firm-specific information. Instead, they argue that no causal stock-bond relationship exists, and the observed contemporaneous correlation between stock and bond returns only reveals their joint reaction to common factors.

Consistent with Kwan (1996) and Hotchkiss and Ronen (2002), I find stock returns are positively correlated with contemporaneous bond returns with a correlation coefficient of 0.154, suggesting that at the individual firm level, information that drives individual stock and bond returns is primarily related to the mean value of the firm’s asset, not the volatility of asset returns. Also consistent with Blume, Keim and Patel (1991) and Cornell and Green (1991), high-yield bonds are not sensitive to movements in interest rates (as the coefficient for DR_t is not significant) but are very sensitive to changes in stocks prices. The coefficient for MR_t is 0.1081, and is significant at 5% level.

As to the leads and lags, Table 1.3 shows that lagged stock returns have explanatory power for current bond returns, with the coefficients significant at 1% level back to day t-5. Furthermore, Granger causality test rejects the null hypothesis that the coefficients for SR_{t-1} through SR_{t-5} are zero at 1% level. Therefore, there is strong evidence that the stock market contains valuable information about future bond returns. This result is consistent with the stock lead found in Kwan (1996).

16 For more detailed information about FIPS, see the NASD NtM 94-23, Alexander, Edwards, and Ferri (1999, 2000), and Hotchkiss and Ronen (2002).

What differentiates my study from previous ones is the finding that current stock returns are positively correlated with lagged bond returns (Table 1.4). Coefficients for lagged bond returns are both economically and statistically significant, not only for day t-1, but for day t-2 and day t-3. The F-value for testing that $\beta_{12,t-j}$ equals zero for j=1, 2, 3, 4 and 5 is 3.9121, significant at 1% level. This empirical result, together with the anecdotal evidence introduced above, confirm my claim that information-based trading also takes place in the high-yield corporate bond market.

The reason that this relationship is not found in Kwan (1996) might be attributed to the quality of the data he uses. First, it is hard to identify active bonds using quotes data from a dealer, even though small issues that are subject to infrequent trading are eliminated from the sample. In fact, the use of inactive bonds to examine the lead-lag relations might bias his results toward the stock lead. Second, since information (especially publicly released information) is impounded into prices quickly, using data on weekly frequency to address the price discovery process is also questionable.

The reason that my results are also different from Hotchkiss and Ronen (2002) is probably due to the fact that they are focusing on the lead-lag relationships at the portfolio level, given that the quality of FIPS data they use is close to the TRACE 50 data in the current study. They first construct a portfolio of the 20 most frequently traded FIPS bonds which were issued by public companies, and then conduct an analysis of Granger causality between portfolios of the FIPS bonds and of the corresponding stocks. Since aggregation across different bonds and stocks into

Table 1.3 Regression of current bond returns on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 48 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0015	3.4504	0.0006
2	DR	0.0482	0.9116	0.3620
3	MR	0.1081	4.4336	0.0000
4	SR{1}	0.1410	20.3446	0.0000
5	SR{2}	0.0887	12.4303	0.0000
6	SR{3}	0.0473	6.5836	0.0000
7	SR{4}	0.0264	3.7171	0.0002
8	SR{5}	0.0182	2.5803	0.0099
9	BR{1}	-0.3014	-24.3606	0.0000
10	BR{2}	-0.1520	-11.8846	0.0000
11	BR{3}	-0.0899	-7.0288	0.0000
12	BR{4}	-0.0680	-5.4416	0.0000
13	BR{5}	-0.0632	-5.4159	0.0000
14	AS{1}	-0.0006	-0.9793	0.3275
15	AS{2}	0.0006	0.7520	0.4521
16	AS{3}	-0.0001	-0.0875	0.9303
17	AS{4}	-0.0002	-0.3191	0.7497
18	AS{5}	0.0007	1.1255	0.2604
19	OS{1}	-0.0382	-1.0249	0.3054
20	OS{2}	-0.0328	-0.7880	0.4307
21	OS{3}	0.0349	0.8386	0.4017
22	OS{4}	0.0367	0.8842	0.3766
23	OS{5}	-0.0265	-0.7091	0.4783
24	Adj R-Square	0.1521		

Table 1.3 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
SR: Lag 1 to Lag 5	132.7280	0.0000
AS: Lag 1 to Lag 5	0.5171	0.7635
OS: Lag 1 to Lag 5	2.5503	0.0259

Panel A presents the results from estimating the following model:

$$BR_{i,t} = \alpha_2 + \gamma_{21} MR_t + \gamma_{22} DR_{i,t} + \sum_{j=1}^{5} \beta_{21,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{22,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{23,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{24,-j} OS_{i,t-j} + \varepsilon_{i2,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{21}, β_{23}, *and* β_{24} *are equal to zero.*

portfolios could possibly remove information about informed trading in stocks and bonds at the individual firm level, lead-lag relationships on the firm level are not specifically addressed in their study and hence constitute one of the major topics for this paper.

Moreover, the evidence that both lagged stock returns and lagged bond returns predict current prices movements implies that it takes time for new information to become incorporated into security prices. Compared to the corporate bond market, the stock market is informationally more efficient. According to the results reported in Table 3, lagged stock returns only for time t-1 is statistically significant at the 5%

Table 1.4: Regression of current stock returns on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 48 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0016	2.4145	0.0158
2	DR	-0.1086	-1.2622	0.2069
3	MR	1.3096	32.9130	0.0000
4	SR{1}	0.1823	16.1368	0.0000
5	SR{2}	-0.0094	-0.8059	0.4203
6	SR{3}	-0.0197	-1.6679	0.0954
7	SR{4}	-0.0195	-1.6764	0.0937
8	SR{5}	0.0219	1.9043	0.0569
9	BR{1}	0.0404	2.0034	0.0452
10	BR{2}	0.0851	4.1485	0.0000
11	BR{3}	0.0363	1.7699	0.0768
12	BR{4}	0.0287	1.4297	0.1529
13	BR{5}	0.0037	0.1921	0.8477
14	AS{1}	-0.0027	-2.5129	0.0120
15	AS{2}	0.0004	0.3540	0.7233
16	AS{3}	0.0016	1.2257	0.2204
17	AS{4}	0.0014	1.1121	0.2661
18	AS{5}	-0.0002	-0.1651	0.8689
19	OS{1}	-0.0529	-0.8697	0.3845
20	OS{2}	-0.0027	-0.0382	0.9695
21	OS{3}	0.0206	0.2952	0.7678
22	OS{4}	-0.0223	-0.3199	0.7491
23	OS{5}	0.0241	0.3954	0.6926
24	Adj R-Square	0.1639		

Table 1.4 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
BR: Lag 1 to Lag 5	3.9121	0.0015
AS: Lag 1 to Lag 5	2.3846	0.0360
OS: Lag 1 to Lag 5	1.0243	0.4013

Panel A presents the results from estimating the following model:

$$SR_{i,t} = \alpha_1 + \gamma_{11} MR_t + \gamma_{12} DR_{i,t} + \sum_{j=1}^{5} \beta_{11,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{12,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{13,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{14,-j} OS_{i,t-j} + \varepsilon_{i1,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{12}, β_{13}, *and* β_{14} *are equal to zero.*

level, and the magnitude drops dramatically after time t-1, while lagged bond returns are statistically significant for both time t-1 and t-2, with even much higher magnitude for time t-2. This indicates that information gets impounded in stock prices within one day, while it takes the corporate bond market much longer to adjust to the new information, a conclusion that differs from Hotchkiss and Ronen (2002) where they argue that market quality is no poorer for bonds than for their underlying stocks.

To summarize, even though the stock market and the bond market differ in degree of informational efficiency, an informed trader trades in both the stock market and the high-yield corporate bond market on their private information, and both markets serve important informational roles in the price discovery process.

Bond-option relationships

Compared to a small body of work on the stock-bond interrelation, literature on whether the corporate bond market also contains important information as to future movements in the option market is literally blank. Following Beckers (1981), who suggests that ATM options contain most of the relevant information in predicting future market volatility, most empirical studies on the links between options and equity markets focus on data for at- and near-the-money options. Chakravarty, Gulen and Mayhew (2004) find that on average, the information share of the price discovery process tends to be higher for OTM options than ATM options. Furthermore, as corporate bonds embed a short position in OTM put options on credit risk, it is very natural to check the OTM option market. In this paper, I use the bid-ask spreads in both OTM and ATM put options as a measure of information-based trading on the options market.

Table 1.3, 1.5 and 1.6 establish a very interesting relation between the corporate bond market and the option market. Even though none of the coefficients for lagged deep OTM put spreads are significant in explaining current bond returns (Table 1.3), Granger causality tests do reject the null hypothesis that lagged OTM spreads, as a whole, have no explanatory power (with an F-value 2.5503 and a significance level of 0.0259). On the other hand, as shown by Table 1.6, when current deep OTM put option spreads are regressed on lagged bond returns, none of the coefficients are significant at any sensible level. Furthermore, Granger causality tests cannot reject that all coefficients are equal to zero. Therefore, OTM put spreads contain valuable information that can help to predict future bond returns, indicating that investors prefer to trade OTM options rather than high-yield corporate bonds.

The option lead, however, is not confirmed when I examine the relationship between bonds and ATM options. Table 1.3 shows that lagged ATM put option spreads have no explanatory power for current bond returns. Thefore, if an informed investor obtains some information that will affect the value of both corporate bonds and options, trading OTM options is her first choice. This is because for delta-equivalent positions, deep OTM put options are more subject to a crash in a firm's value than ATM options. As a result, informed traders who obtain very bad news about a firm will prefer to buy OTM puts on the firm's stock, which will be reflected in the bid-ask spreads. On the other hand, since corporate bonds embed a short position in OTM puts, only information about a possible crash in the firm's value, and hence default in future interests and principal payments will affect the bond price. Therefore, the evidence of OTM put option spreads predicting future bond returns indicates that the option market is leading the bond market in reflecting extreme firm-specific information. This explanation from the perspective of the nature of private information can be further strengthened by the lead-lag relations between options and stocks discussed in the following subsection.

Stock-option relationships

To complete the examination of information flow across stocks, bonds and options, I check whether the option market contains valuable information about future stock returns. Following seminal work by Black (1975), there has been a huge literature

Table 1.5: Regression of current ATM put option spreads on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 48 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0570	9.6733	0.0000
2	DR	-0.4610	-0.4979	0.6186
3	MR	1.2476	2.8417	0.0045
4	SR{1}	-0.1172	-0.8746	0.3818
5	SR{2}	-0.0381	-0.2496	0.8029
6	SR{3}	0.0246	0.1583	0.8742
7	SR{4}	-0.1119	-0.7449	0.4563
8	SR{5}	0.0057	0.0420	0.9665
9	BR{1}	0.1325	0.5591	0.5761
10	BR{2}	0.3471	1.4638	0.1433
11	BR{3}	0.0462	0.1902	0.8491
12	BR{4}	0.5185	2.2185	0.0266
13	BR{5}	-0.0036	-0.0161	0.9872
14	AS{1}	1.0232	82.4139	0.0000
15	AS{2}	-0.3624	-20.4031	0.0000
16	AS{3}	0.2108	11.5775	0.0000
17	AS{4}	-0.0872	-4.8705	0.0000
18	AS{5}	0.0557	4.4403	0.0000
19	OS{1}	-0.3159	-0.4433	0.6576
20	OS{2}	0.2105	0.2154	0.8295
21	OS{3}	0.6640	0.6836	0.4943
22	OS{4}	-0.9196	-0.9414	0.3465
23	OS{5}	1.1852	1.6523	0.0985
24	Adj R-Square	0.4830		

Table 1.5 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
SR: Lag 1 to Lag 5	0.3682	0.8706
BR: Lag 1 to Lag 5	1.3770	0.2295
OS: Lag 1 to Lag 5	7.0489	0.0000

Panel A presents the results from estimating the following model:

$$AS_{i,t} = \alpha_3 + \gamma_{31} MR_t + \gamma_{32} DR_{i,t} + \sum_{j=1}^{5} \beta_{31,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{32,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{33,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{34,-j} OS_{i,t-j} + \varepsilon_{i3,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{31}, β_{32}, *and* β_{34} *are equal to zero.*

studying inter-market relationships between equity and equity derivative markets. As suggested by Black (1975), the option market might be more attractive to informed traders than the market for the underlying stock because options offer higher financial leverage, and the option market is characterized by less stringent margin requirements, no uptick rule for short selling, and probably lower transaction costs. Whether the option market is leading the stock market in reflecting new information has been

Table 1.6: Regression of current OTM put option spreads on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 48 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0002	2.0223	0.0432
2	DR	-0.0102	-0.6509	0.5151
3	MR	0.0169	2.2759	0.0229
4	SR{1}	0.0027	1.1792	0.2384
5	SR{2}	0.0027	1.0148	0.3102
6	SR{3}	0.0009	0.3306	0.7410
7	SR{4}	0.0015	0.5689	0.5694
8	SR{5}	0.0021	0.8884	0.3744
9	BR{1}	0.0008	0.2023	0.8397
10	BR{2}	-0.0013	-0.3050	0.7603
11	BR{3}	-0.0016	-0.3749	0.7078
12	BR{4}	-0.0010	-0.2455	0.8061
13	BR{5}	-0.0044	-1.1453	0.2521
14	AS{1}	0.0001	0.2999	0.7643
15	AS{2}	-0.0002	-0.6350	0.5255
16	AS{3}	0.0002	0.7181	0.4728
17	AS{4}	0.0001	0.2940	0.7688
18	AS{5}	0.0000	0.1593	0.8735
19	OS{1}	0.9952	81.1621	0.0000
20	OS{2}	-0.3339	-19.3703	0.0000
21	OS{3}	0.3232	18.7878	0.0000
22	OS{4}	-0.1152	-6.6814	0.0000
23	OS{5}	0.1199	9.7091	0.0000
24	Adj R-Square	0.9231		

Table 1.6 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
BR: Lag 1 to Lag 5	1.6781	0.1361
AS: Lag 1 to Lag 5	0.3417	0.8878
OS: Lag 1 to Lag 5	0.8776	0.4951

Panel A presents the results from estimating the following model:

$$OS_{i,t} = \alpha_4 + \gamma_{41} MR_t + \gamma_{42} DR_{i,t} + \sum_{j=1}^{5} \beta_{41,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{42,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{43,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{44,-j} OS_{i,t-j} + \varepsilon_{i4,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{41}, β_{42}, *and* β_{43} *are equal to zero.*

directly examined in numerous empirical studies[17]. Panton (1976) takes the first step

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17 The stock-option link and the role of the options market in the price discovery process have also been addressed indirectly from many perspectives. Early accounting research shows that current option prices reflect market anticipation of forthcoming earnings announcements and predict future stock price variability [Patell and Wolfson (1979, 1981)]. The informational role of options markets are further investigated in the financial markets literature. Jennings and Starks (1986) find that the stock prices of firms with listed options adjust to earnings announcements faster than those of nonoption firms and they conclude that options markets help to disseminate earnings news. Grossman (1988) argues that option trading reveals the future trading intentions of investors, and therefore helps to predict future price volatility. By comparing return patterns in contemporaneous stock and options, as well as options that are adjusted for contemporaneous changes in the price and volatility of the underlying asset, Sheikh and Ronn (1994) confirm informed trading in options markets. Figlewski and Webb (1993) show that options increase both transactional and informational efficiency of the market for the underlying stocks by reducing the effect of short selling constraints. A less-related literature examines hedging-related effects of option trading and their implications for inter-market linkages. When the complete market assumption under standard option pricing models is relaxed, introduction of options alters investors' hedging opportunities. The value of the underlying stocks increases while excess return volatility declines. This phenomenon has been documented in several empirical studies (Nabar and Park (1988), Skinner (1989), Conrad (1989)) and is subsequently formalized by DeTemple and Selden (1991) in a

in this direction, but he fails to demonstrate conclusively that call options are in general valid predictors of future stock price changes. Based on the Black-Scholes option pricing model, Latane and Rendleman (1976) and Beckers (1981) derive the volatility implied in option prices and show that it predicts future stock price variability. The leading role of the option market is strengthened by Manaster and Rendleman (1982), where they compare the implied and observed stock prices and demonstrate that the implied stock prices contain valuable information about the equilibrium prices of the underlying stocks that has not been revealed in the stock market. Furthermore, Fleming, Ostdiek and Whaley (1996) compare the transaction costs in the stock and the option markets, and show that for individual stocks, price discovery happens in the stock market as it offers lower spreads and higher liquidity. However, Vijh (1988) argues that the result of Manaster and Rendleman (1982) is questionable, since using daily closing prices introduces a bias associated with the bid-ask spread and nonsynchronous trading. After purging the effects of bid-ask spreads, Stephan and Whaley (1990) find that the stock market leads the option market. Nevertheless, Chan et al. (1993) argue that the stock lead is due to the relative smaller stock tick. If the average of the bid and ask is used instead of the transaction price, neither market leads the other.

While most work by middle 90s investigate the price relation between stocks and options, recently studies on the lead-lag relation have been focused more on

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theoretical model. While most studies confirm the important role of options markets in the general price formation process, two exceptions stand out. Bhattacharya (1987) tries to compare implied bid and ask stock prices, which are derived from options quotes, to observed bid and ask stock prices to identify arbitrage opportunities. He fails to find any profitable trading strategies and hence cannot reject the null hypothesis that option prices bear no additional information over that contained in contemporaneous stock prices. By examining the depth and bid-ask spreads of the Chicago Board Options Exchange (CBOE), Vijh (1990) shows that the options market is not dominated by informed traders.

trading volume[18]. Easley et al. (1998) show that "positive news option volumes" and "negative news option volumes" have predictive power for future stock price changes. The predictive ability of option trading volume is subsequently confirmed by Pan and Poteshman (2003), but not by Chan, Chung and Fong (2002). Cao, Chen and Griffin (2003) find that option volume imbalances are informative in the presence of pending extreme information events, but they fail to identify the same information role for option volume during normal periods. By measuring the relative share of price discovery occurring in the stock and options markets, Chakravarty, Gulen and Mayhew (2004) conclude that informed trading takes place in both stock and option markets, suggesting an important informational role for option volume. Following Chan, Chung and Fong (2002), who suggest that option quote revisions contain information about future price movements, this study uses bid-ask spreads for both ATM and deep OTM options. Consistent with Chan, Chung and Fong (2002), I find an informational role for option quote revisions. Table 1.4 shows that current stock returns are negatively correlated with ATM put spreads for the previous day, and lagged ATM put option spreads Granger cause current stock returns (F-value of 2.3846, significant at 5% level). Since lagged stock returns have no explanatory power for current ATM put spreads, it is safe to conclude that trading in options leads trading in the underlying stocks, with a one-day lag. This conclusion complements the findings of a one-day lead of options by Manaster and Rendleman (1982) based on transaction price data, and that of Anthony (1988) with volume data. It also supports the argument that informed traders might submit limit orders in the option market to exploit their private information.

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18 Trading volume relations in the stock and options markets have been explored by Anthony (1988) and Stephan and Whaley (1990). While Anthony (1988) finds weak evidence of the option lead based on a daily dataset, Stephan and Whaley (1990) use intraday transaction data and draw an opposite conclusion. However, using total call option volume over a certain period of time is subject to question as its information content is hard to interpret.

Interestingly, the leading role of option quote revisions can not be confirmed by deep OTM options. Lagged deep OTM put spreads do not predict current stock returns (Table 1.4), nor are lagged stock returns correlated with current OTM spreads (Table 1.6). This result contradicts that of Chakravarty, Gulen and Mayhew (2004), where they argue the average information share is significantly higher for OTM options than for ATM options. If the higher information share for OTM options in the price discovery process can be attributed to their higher leverage, the superior predictive power of ATM option spreads might reside in their tighter bid-ask spreads compared to OTM options. However, this explanation is not very convincing as informed traders tend to submit limit orders in the option market to avoid higher options spreads relative to those of stocks.

The finding that current stock returns can be predicted by lagged spreads for ATM puts but not OTM puts can be explained by the kind of information investors trade on. Compared to deep OTM put options, ATM puts are more sensitive to changes in the mean value of a firm's assets, especially when the changes are not dramatic. Therefore, unless there is "crash" information about the firm's value, which will change the moneyness of the deep OTM put options, informed traders are more likely to trade ATM options. The clustering of informed trading in ATM options makes ATM option spreads capable of predicting future stock price changes, leading to the conclusion that the option market is leading the stock market in reflecting mild firm-specific information. The identification of a unidirectional relation of ATM options leading stocks complements the finding that OTM options lead corporate bonds in displaying how an informed trader's choice of options of different moneyness depends on the type of information she possesses. If she has some mild information, she will trade in at-the-money options; however, if she has some extreme information, she will trade in deep out-of-the-money options. This finding contributes to a strand of literature on how information based trading in the option market is allocated across strike prices [De Jong, Koedijk, and Schnitzlein (2001), Kaul, Nimalendran and Zhang (2002), Anand and Chakravarty (2003), Chakravarty, Gulen, Mayhew (2004)].

Infrequent Trading and the Lead-Lag Relationships

In this section, the panel VAR model is re-estimated based on data for all 77 firms to examine whether the results in the previous section are subject to infrequent trading in corporate bonds. As shown by Table 1.1 and Table 1.2, firms with inactive bonds tend to be smaller than firms with active bonds. Reinserting those small firms and examining the pairwise lead-lag effects allows us to see whether an informed trader's choice to trade high-yield corporate bonds depends on the issuer's size, and how the dynamics of information flow across different securities varies with firm size. The results are presented in Table 1.7 through Table 1.10.

Stock returns are still positively correlated with contemporaneous bond returns at 0.143. The explanatory power of past bond returns remains, with $\beta_{12,-j}$ estimated at 0.0403, 0.0852 and 0.0362 respectively for j=1, 2, and 3. All estimates are statistically significant at 5% level except for that of time t-3, which is significant at 10%. In addition, Granger causality tests confirm additional predictive power added by lagged bond returns, with an F-value of 3.8959, which is significant at 1% level. Since higher

Table 1.7: Regression of current stock returns on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 77 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0002	2.4229	0.0154
2	DR	-0.0063	-1.1805	0.2379
3	MR	0.0173	32.7755	0.0000
4	SR{1}	0.0027	16.2631	0.0000
5	SR{2}	0.0026	-0.8512	0.3947
6	SR{3}	0.0011	-1.6758	0.0938
7	SR{4}	0.0012	-1.6556	0.0978
8	SR{5}	0.0022	1.8647	0.0623
9	BR{1}	0.0010	1.9932	0.0463
10	BR{2}	-0.0015	4.1436	0.0000
11	BR{3}	-0.0012	1.7636	0.0779
12	BR{4}	-0.0011	1.4180	0.1563
13	BR{5}	-0.0043	0.2297	0.8183
14	AS{1}	0.0001	-2.5685	0.0102
15	AS{2}	-0.0002	0.3814	0.7029
16	AS{3}	0.0002	1.2717	0.2035
17	AS{4}	0.0001	1.1099	0.2671
18	AS{5}	0.0001	-0.2296	0.8184
19	OS{1}	1.0105	-0.8147	0.4153
20	OS{2}	-0.3567	-0.0297	0.9763
21	OS{3}	0.3430	0.3230	0.7467
22	OS{4}	-0.1318	-0.3703	0.7112
23	OS{5}	0.1241	0.3702	0.7112
24	Adj R-Square	0.1635		

Table 1.7 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
BR: Lag 1 to Lag 5	3.8959	0.0016
AS: Lag 1 to Lag 5	2.4465	0.0318
OS: Lag 1 to Lag 5	0.9664	0.4368

Panel A presents the results from estimating the following model:

$$SR_{i,t} = \alpha_1 + \gamma_{11} MR_t + \gamma_{12} DR_{i,t} + \sum_{j=1}^{5} \beta_{11,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{12,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{13,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{14,-j} OS_{i,t-j} + \varepsilon_{i1,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{12}, β_{13}, *and* β_{14} *are equal to zero.*

frequency of trading in stocks as compared to bonds tends to introduce a spurious stock lead, the fact that the predictive ability of previous bond returns for present stock prices changes remains even for firms with inactive bonds makes my results very strong.

The fact that investors might choose to trade on their private information in the corporate bond market has important implications for surveillance for illegal insider trading in this market. While this study does not investigate whether corporate bond traders are trading on insider information unlawfully or aim at establishing a breach of fiduciary duty, it is likely that some of the information that informed traders exploit is

Table 1.8: Regression of current bond returns on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 77 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0015	3.4360	0.0006
2	DR	0.0526	0.9864	0.3240
3	MR	0.1080	4.4177	0.0000
4	SR{1}	0.1411	20.3171	0.0000
5	SR{2}	0.0892	12.4718	0.0000
6	SR{3}	0.0478	6.6383	0.0000
7	SR{4}	0.0266	3.7420	0.0002
8	SR{5}	0.0182	2.5735	0.0101
9	BR{1}	-0.3066	-24.7193	0.0000
10	BR{2}	-0.1533	-11.9384	0.0000
11	BR{3}	-0.0904	-7.0384	0.0000
12	BR{4}	-0.0684	-5.4452	0.0000
13	BR{5}	-0.0634	-5.4190	0.0000
14	AS{1}	-0.0006	-0.9544	0.3399
15	AS{2}	0.0006	0.7225	0.4700
16	AS{3}	-0.0001	-0.0923	0.9265
17	AS{4}	-0.0002	-0.3188	0.7499
18	AS{5}	0.0007	1.1363	0.2559
19	OS{1}	-0.0370	-0.9886	0.3229
20	OS{2}	-0.0328	-0.7870	0.4313
21	OS{3}	0.0339	0.8120	0.4168
22	OS{4}	0.0369	0.8881	0.3745
23	OS{5}	-0.0270	-0.7188	0.4723
24	Adj R-Square	0.1520		

Table 1.8 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
SR: Lag 1 to Lag 5	132.1312	0.0000
AS: Lag 1 to Lag 5	0.5083	0.7702
OS: Lag 1 to Lag 5	2.2486	0.0468

Panel A presents the results from estimating the following model:

$$BR_{i,t} = \alpha_2 + \gamma_{21} MR_t + \gamma_{22} DR_{i,t} + \sum_{j=1}^{5} \beta_{21,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{22,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{23,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{24,-j} OS_{i,t-j} + \varepsilon_{i2,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{21}, β_{23}, and β_{24} are equal to zero.

illegal in nature. If prices of corporate bonds are sensitive to private information and the market for corporate bonds, especially high-yield bonds, includes some insider trading, then the concerns about insider trading as in any other securities market apply. It might be optimal for both policymakers and regulators to devote more efforts in monitoring the corporate bond market.

As to the relationships between the option market and the other two markets, ATM put option spreads continue to lead stock returns. The hypothesis that current stock returns have predictive power for future ATM put spread changes can be easily rejected, with an F-value of 0.3838 (Table 1.9). The hypothesis on the ATM option

Table 1.9: Regression of current ATM put option spreads on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 77 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0569	9.6685	0.0000
2	DR	-0.3933	-0.4239	0.6717
3	MR	1.2400	2.8338	0.0046
4	SR{1}	-0.1203	-0.9023	0.3669
5	SR{2}	-0.0313	-0.2067	0.8362
6	SR{3}	0.0283	0.1827	0.8551
7	SR{4}	-0.1169	-0.7831	0.4336
8	SR{5}	0.0013	0.0098	0.9922
9	BR{1}	0.1094	0.4638	0.6428
10	BR{2}	0.3585	1.5203	0.1285
11	BR{3}	0.0393	0.1631	0.8705
12	BR{4}	0.5490	2.3615	0.0182
13	BR{5}	-0.0169	-0.0759	0.9395
14	AS{1}	1.0248	82.2767	0.0000
15	AS{2}	-0.3623	-20.3270	0.0000
16	AS{3}	0.2106	11.5677	0.0000
17	AS{4}	-0.0867	-4.8554	0.0000
18	AS{5}	0.0540	4.3073	0.0000
19	OS{1}	-0.3204	-0.4508	0.6522
20	OS{2}	0.2860	0.2938	0.7689
21	OS{3}	0.6454	0.6672	0.5047
22	OS{4}	-0.7887	-0.8109	0.4175
23	OS{5}	0.9964	1.3938	0.1634
24	Adjusted R-Square	0.4870		

Table 1.9 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	p-value
SR: Lag 1 to Lag 5	0.3838	0.8602
BR: Lag 1 to Lag 5	1.4924	0.1887
OS: Lag 1 to Lag 5	6.8842	0.0000

Panel A presents the results from estimating the following model:

$$AS_{i,t} = \alpha_3 + \gamma_{31} MR_t + \gamma_{32} DR_{i,t} + \sum_{j=1}^{5} \beta_{31,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{32,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{33,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{34,-j} OS_{i,t-j} + \varepsilon_{i3,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{31}*,* β_{32}*, and* β_{34} *are equal to zero.*

lead in the stock-option relationship, however, can not be rejected (Table 1.7). Furthermore, the result concerning the correlation between present bond returns and earlier OTM option spreads is robust even when infrequently traded bonds are considered. Table 8 shows lagged deep OTM options spreads contain valuable information about current bond price changes, with Granger causality test rejecting the null hypothesis that the coefficients for AS_{t-1} through AS_{t-5} are zero at 1% level. However, none of the lagged bond returns are significant in explaining current OTM option spreads, making my conclusion on the option’s lead even stronger.

Table 1.10: Regression of current OTM put option spreads on current default-free debt returns, market returns, lagged bond returns, lagged ATM put option spreads, and lagged deep OTM put option spreads for the 77 firms with frequently traded bonds

Panel A: Estimation Results

	Variable	Est.	t-value	p-value
1	Constant	0.0002	2.0052	0.0450
2	DR	-0.0063	-0.4008	0.6886
3	MR	0.0173	2.3276	0.0200
4	SR{1}	0.0027	1.1858	0.2357
5	SR{2}	0.0026	0.9656	0.3343
6	SR{3}	0.0011	0.3900	0.6965
7	SR{4}	0.0012	0.4531	0.6505
8	SR{5}	0.0022	0.9273	0.3538
9	BR{1}	0.0010	0.2433	0.8078
10	BR{2}	-0.0015	-0.3609	0.7182
11	BR{3}	-0.0012	-0.2816	0.7783
12	BR{4}	-0.0011	-0.2635	0.7921
13	BR{5}	-0.0043	-1.1234	0.2613
14	AS{1}	0.0001	0.2492	0.8032
15	AS{2}	-0.0002	-0.5366	0.5916
16	AS{3}	0.0002	0.7155	0.4743
17	AS{4}	0.0001	0.1883	0.8507
18	AS{5}	0.0001	0.2418	0.8089
19	OS{1}	1.0105	82.1563	0.0000
20	OS{2}	-0.3567	-20.4802	0.0000
21	OS{3}	0.3430	19.7159	0.0000
22	OS{4}	-0.1318	-7.5642	0.0000
23	OS{5}	0.1241	10.0197	0.0000
24	Adj. R-Square	0.9230		

Table 1.10 (Continued)

Panel B: Granger Causality Tests

Null Hypothesis : The Following Coefficients Are Zero	F-value	Significance Level
SR: Lag 1 to Lag 5	1.4603	0.1993
BR: Lag 1 to Lag 5	0.3573	0.8778
AS: Lag 1 to Lag 5	0.8832	0.4913

Panel A presents the results from estimating the following model:

$$OS_{i,t} = \alpha_4 + \gamma_{41} MR_t + \gamma_{42} DR_{i,t} + \sum_{j=1}^{5} \beta_{41,-j} SR_{i,t-j} + \sum_{j=1}^{5} \beta_{42,-j} BR_{i,t-j} + \sum_{j=1}^{5} \beta_{43,-j} AS_{i,t-j} + \sum_{j=1}^{5} \beta_{44,-j} OS_{i,t-j} + \varepsilon_{i4,t}$$

SR and BR represent daily stock return and bond return, calculated from end-of-day closing prices. MR is the S&P 500 index return, and DR denotes return on a default-free debt with future cash flows matched perfectly with the high-yield corporate bond. AS and OS stand for ATM put options spreads and OTM put options spreads respectively. They are normalized by dividing the bid-ask spreads by the average of bid and ask quotes. Panel B contains the results from Granger Causality tests on whether all β_{41}, β_{42}, *and* β_{43} *are equal to zero.*

Conclusions and Extensions

Taking advantage of a unique corporate bond transaction dataset from NASD, this paper studies whether information-based trading takes place in the high-yield corporate bond market, and how firm-specific information flow across three important securities, stocks, options and corporate bonds, whose value is related to the issuer's underlying assets. In contrast to previous studies [Kwan (1996), Hotchkiss and Ronen (2002)], I find that informed traders do trade in the corporate bond market, and corporate bond returns contain important information about future stock price movements. Both the stock market and the bond market serve important informational roles in the price discovery process. Furthermore, compared to the stock and the bond markets, the option market is a preferred venue for informed trading. It is leading both the stock market and the corporate bond markets in reflecting firm specific information. In addition, there is strong evidence that an informed trader's choice of options with different strike prices depends crucially on what kind of information she has. Unless she is aware of some impending extreme event to a firm, in which case she rushes to buy deep OTM put options on the firm, she will trade ATM options if she obtains milder information.

The analysis of the dynamics of information flow across individual stocks, options and corporate bonds can be extended in several important ways. First, it is interesting to extend this study in both cross-sectional and time-series frameworks. What this study establishes is a world with asymmetric information arrival, with the option market leading the others. It would be interesting to know whether this relationship extends to each individual firm, and if not, how it varies with firm-specific characteristics. Furthermore, how the relative speed of adjustment to new information in different markets changes with contemporaneous market conditions and over time, and whether it differs dramatically between event days and non-event days are of no less interest. Answers to these questions will provide deeper understanding of the price discovery process. An example of work in this direction is Chakravarty, Gulen and Mayhew (2004).

Second, as this study focuses on the lead-lag interrelationships between three closely related securities markets in terms of price, it is equally important to explore the information role of volume. Easley and O'Hara (1992) show that volume contains some information that is not reflected in the price. Blume, Easley and O'Hara (1994) emphasize the role of volume as a statistic for technical analysis. It is interesting to check whether transaction volume in different markets provides additional insights into where informed traders trade and where price discovery takes place. Furthermore, an investigation of the pattern of trading volume in corporate bonds and its time-series variation would contribute to the new area of corporate bond market microstructure.

Third, the identification of informed trading in the high-yield bond market suggests a market microstructure approach to corporate bond pricing. Traditional models of default, including both option-based structural models and reduced form models, have had limited success in explaining the corporate yield spreads observed in actual markets. Even after accounting for liquidity effects, it is still challenging to explain credit spread changes solely based on credit-risk factors [see for example, Collin-Dufresne, Goldstein and Martin (2001), Eom, Helwege and Huang (2003), Duffie and Singleton (2003) and Huang and Huang (2003)]. One inherent assumption under all these models, however, is that the market is complete. If information is asymmetric, then informed traders are better able to adjust their portfolio to incorporate new information, putting uninformed traders at a disadvantage. In equilibrium, investors require higher yield to hold bonds with greater information-based trading. This suggests that in addition to traditional corporate bond pricing factors, risks associated with informed trading are also priced in corporate bonds. The high-yield spreads observed in the market might embed an information premium that is ignored by existing corporate bond pricing models, and correct pricing of information risk in the corporate bond market brings a more ambitious goal into research agenda.

Lastly, as posited by Titman (2002), if the markets for debt, equity and derivatives are not integrated, then the required return premium associated with any risk differs across markets. This directly affects how firms raise capital and hedge. The complete transaction dataset for debt, equity and derivative securities, as well as an accurate pricing model for different risks, allow direct tests of whether the markets for these securities are perfectly integrated, and hence help us to gain a deeper understanding of the Modigliani and Miller (1958) theorem.

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CHAPTER 2

INFORMATION, LIQUIDITY AND CORPORATE YIELD SPREADS

Introduction

Traditional structural models of default risk, built on the original insights of Black and Scholes (1973) and Merton (1974), provide an intuitive framework for identifying the determinants of yield spread of risky debt securities. According to Merton (1974), corporate debt can be valued as a portfolio comprised of similar risk free debt and a short position in a put option on the issuer's assets. This option-based approach has been extended in numerous theoretical studie[19] to incorporate realistic economic considerations. For example, Longstaff and Schwartz (1995) propose a tractable model which incorporates both default risk and interest rate risk and allows for deviations from strict absolute priority. Anderson and Sundaresan (1996) and Mella-Barral and Perraudin (1997) factor strategic debt service into the premium on risky corporate debt. Leland and Toft (1996) relax the assumption of the exogenously–determined default boundaries, and Collin-Dufresne and Goldstein (2001) improve on the structural approach by allowing the firms to adjust their capital structure to reflect changes in asset value.

Despite the richness of this structural paradigm, practical applications have been disappointing. Several empirical analyses [see for example, Jones, Mason and

[19] See Anderson and Sundaresan (1996), Black and Cox (1976), Collin-Dufresne and Goldstein (2001), Duffie and Lando (2001), Geske (1977), Ingersoll (1977), Kim, Ramaswamy and Sundaresan (1993), Leland (1994, 1998), Leland and Toft (1996), Longstaff and Schwartz (1995), Mella-Barral and Perraudin (1997) and Zhou (2001).

Rosenfeld (1984)] have shown that the Corporate-Treasury yield spreads generated by the original Merton (1974) model are significantly below those observed in the market. Additionally, tests of other structural models have not yet reached any consensus on the ability of these models to explain the observed corporate yield spreads [see Anderson and Sundaresan (2000), Lyden and Saraniti (2000) and Eom, Helwege and Huang (2002)]. Instead, Collin-Dufresne, Goldstein and Martin (2001) find that variables that should theoretically determine credit spread changes actually have rather limited explanatory power. Furthermore, they identify a 'single common factor' that drives most of the changes in yield spreads. This common factor, however, can not be explained by any macroeconomic or financial variables in their study. Moreover, Huang and Huang (2003) conclude that credit risk accounts for only part of the observed Corporate-Treasury yield spreads, leaving the rest again unexplained within the structural framework of credit risk valuation.

Instead of modeling credit risks on the variability of the firm's asset value as in the structural framework, an alternative approach would be reduced form models[20], which value risky bonds by discounting certainty equivalent cash flows at risk free rates. Therefore, the value of a risky bond is directly linked to the default risk and the recovery rate in the event of default, both of which are assumed to be stochastic and exogenous to the model. Compared to structural models, reduced form models are more flexible, and mathematically more tractable. Furthermore, they incorporate several factors other than default risk, such as illiquidity and state taxes, into the stochastic default risk process. However, these models are still unable to fully rationalize actual corporate yield spreads. The unsatisfactory performance of these

[20] See Duffee (1999), Duffie and Singleton (1997, 1999), Das and Tufano (1996), Elton, Gruber, Agrawal and Mann (2001), Lando (1997), Madan and Unal (1998, 2000), Jarrow, Lando and Turnbull (1997), Jarrow and Turnbull (1995).

two basic approaches underscores the weakness of our understanding of corporate bond price behavior.

I will argue in this paper that corporate bond market microstructure factors, including information and liquidity, affect corporate bond yield spreads. Consistent with Chen, Lesmond and Wei (2006), I find that liquidity is an important factor in determining yield spread of risky corporate bonds. But perhaps more important, I also find that the degree of asymmetric information in individual bonds contains significant additional power in explaining corporate yield spreads. This finding suggests that actual corporate yield spreads may incorporate both an information premium and a liquidity premium that are ignored by traditional corporate bond pricing models. It also confirms the general argument made by O'Hara in her 2003 American Finance Association (AFA) Presidential Address regarding the implications of market microstructure for asset pricing: "Markets provide two important functions—liquidity and price discovery…. Asset pricing models need to be recast in broader terms to incorporate the transaction costs of liquidity and the risks of price discovery."[21]

Several authors have noted that the relative liquidities of corporate and Treasury bonds, and the role of liquidity in the pricing of corporate debt has been explored in a host of recent studies.[22] Since illiquidity prevents investors from

[21] See O'Hara (2003), Presidential Address: Liquidity and Price Discovery, Journal of Finance 58, page 1335.

[22] The role of liquidity in the pricing of equity securities has been studied extensively in the literature on the implications of market microstructure for asset pricing. See for example, Amihud (2002), Amihud and Mendelson (1986, 1988), Acharya and Pedersen (2004), Boudoukh and Whitelaw (1993), Brennan and Subrahmanyam (1996), Brennan, Chordia and Subrahmanyam (1998), Chalmers and Kadlec (1998), Chordia, Roll and Subrahmanyam (2000), Haugen and Baker (1996), Chordia, Subrahmanyam and Anshuman (2001), Pastor and Stambaugh (2001), Vayanos (2004) and Hasbrouck (2005). Liquidity in the Treasury markets has also been the topic of numerous studies. See for example, Sarig and Warga (1989), Amihud and Mendelson (1991), Warga (1992), Daves and Ehrhardt (1993), Kamara (1994), Elton and Green (1998), Fleming (2002, 2003), Strebulaev (2002), Krishnamurthy (2002) and Goldreich, Hanke and Nathy (2004).

continuously hedging their risks, a liquidity premium is required for compensation. Because secondary corporate bond transactions take place in the over-the-counter (OTC) market, meaningful quote data is difficult to obtain, making it impossible to directly calculate reliable measures of liquidity, such as the bid-ask spread. Furthermore, quality bond transaction data did not exist before the introduction of the Trade Reporting and Compliance Engine (TRACE)[23] by the National Association of Securities Dealers (NASD). Because of this, empirical research in this area has relied on indirect liquidity measures,[24] including the total amount of a bond issue [Alexander, Edwards and Ferri (2000) and Hong and Warga (2000)], coupon rate [Gehr and Martell (1992)], whether the issuer's equity is publicly traded [Alexander, Edwards and Ferri (2000)], age of a bond [Alexander, Edwards and Ferri (2000), Hong and Warga (2000) and Elton, Gruber, Agrawal and Mann (2002)], price volatility of a bond [Alexander, Edwards and Ferri (2000) and Hong and Warga (2000)] and number of market participants quoting the bond [Gehr and Martell (1992)].[25] Houweling, Mentink and Vorst (2003) propose two additional measures: the occurrence of 'price runs'[26] or missing values, and the dispersion of yields quoted from different sources[27]. They show that all of these measures account for some portion of the yield spread changes. Collin-Dufresne, Goldstein and Martin (2001) quantify liquidity effects by using the spread between on- and off-the-run Treasuries, swap spreads and the frequency of quotes versus matrix prices in the Warga database. Furthermore, Longstaff, Mithal and Neis (2004) use the time-series average of the bid-

[23] For a detailed description of the TRACE system, see Zhou (2005a).

[24] In the reduced form approach, liquidity is not modeled specifically to explain corporate yield spreads. Instead, it is subsumed into the stochastic default risk process. Duffee (1999) simply argues that the unexplained part of yields spreads is liquidity based.

[25] For a more complete literature overview of liquidity measures from the empirical bond liquidity literature and their effects on the bond yield, see Houweling, Mentink and Vorst (2003).

[26] 'Price Run' occurs when two consecutive prices for a bond are identical. See Sarig and Warga (1989).

[27] For a detailed description of how to calculate the yield dispersion, see Houweling, Mentink and Vorst (2003).

ask spread reported by Bloomberg, time to maturity of a bond, and dummy variables for bonds issued by financial firms and for bonds issued by highly-rated firms respectively. Chen Lesmond and Wei (2006) uses quarterly bid ask quotes from Bloomberg, as well as percentage of zero return and another liquidity proxy derived from Lesmond, Ogden and Trzcinka (1999). These proxies are demonstrated to be strongly related to the nondefault component of yield spreads[28].

While these different liquidity measures provide more insight into the determinants of yield spread changes, their added explanatory power is rather limited. Moreover, as almost all of these measures investigate the cross-sectional variation in liquidity or liquidity changes at the aggregate level, little is known about how the time-variation in corporate bond liquidity affects yield spreads on an individual basis. Taking advantage of a recent corporate bond transaction data set from the NASD, I use the number of transactions (NOT) and price impact [Amihud (2002)] to measure the liquidity of individual corporate bonds. I find that over time, a low-grade corporate bond's liquidity has significant effects on its yield spread. A one-standard-deviation drop in NOT leads to a widening of the yield spread by more than 13 basis points, and a one-standard deviation increase in price impact raises the yield spread by 52 basis points. This is consistent with previous studies on the liquidity effects on bond yields, and suggests an important liquidity dimension to corporate yield spreads.

Compared to the extensive literature on liquidity effects in asset pricing, research on information risk as a determinant of asset returns is still in its infancy.

[28] Other studies have investigated the exposure of corporate bond returns to liquidity shocks in related markets. De Jong and Driessen (2004) show that corporate bond returns are closely related to changes in the equity market liquidity and Treasury market liquidity. Cremers, Driessen, Maenhout and Weinbaum (2004) look at the liquidity of the market for related individual options and find that the liquidity of the firm's traded options have a significant liquidity-spillover effect on the firm's short-maturity corporate bonds.

During the process of new information becoming incorporated into market prices, the informational advantage of informed traders creates risks for uninformed traders as they constantly lose to the informed ones in the sense that they always end up with portfolios that invest too much in bad assets and too little in good ones. In order for investors to hold securities about which they are uninformed, an information risk premium is required. In a theoretical paper, Easley and O'Hara (2004) develop an asymmetric information asset pricing model and show that a firm's information structure has substantial effects on its cost of capital. An empirical application of this model to the equity market is provided by Easley, Hvidkjaer and O'Hara (2004). Consistent with the prediction of the Easley and O'Hara (2004) model, they find that stocks with more private information and less public information have a higher excess return, all else being equal. Specifically, they identify a 2.5 percent difference in expected annual returns for two stocks with a difference of 10 percentage points in their proxy for information asymmetry, the probability of information-based trading (PIN)[29]. Easley, Hvidkjaer and O'Hara (2004) further confirm the information risk premium in stock returns. After forming composite zero-investment portfolios by taking long positions in high PIN stocks and short positions in low PIN stocks of equal size, they show that these portfolios earn significant excess returns, which cannot be explained by the Fama-French or momentum factors. The conclusion that stock returns embed an information risk premium has also been reached by Burlacu, Fontaine and Jimenez-Garces (2005).

This paper extends the literature on the implications of market microstructure for asset pricing to corporate debt securities and investigates whether corporate yield spreads observed in the market embed an information risk premium. There has been

[29] For PIN estimation details, see Easley, Kiefer and O'Hara (1997).

substantial anecdotal evidence that information-based trading takes place in the corporate bond market. In the late 1980s, investigations by the Securities and Exchange Commission (SEC) and the U.S. Attorney's Office revealed the occurrence of insider trading in the junk bond market by Michael Milken, the "king of junk bonds". In 2000, Donald Trump quietly spent $46 million buying bonds issued by Trump Hotels and Casino Resorts while he threatened to stop payment of interest to investors in his bonds.[30] Furthermore, in 1998, former SEC chairman Arthur Levitt stated that the SEC has "found anecdotal evidence of the possible misuse of inside information in the high-yield (debt) market."[31]

Several studies in market microstructure literature also provide strong empirical evidence of information-based trading in corporate debt securities. Datta and Datta (1996) argue that the absence of any reporting requirement for insider bond transactions may create an enhanced opportunity for insiders to exploit private information to expropriate wealth from uninformed bond traders. In a companion paper [Zhou (2005a)], I find that current high-yield bond returns have explanatory power for future stock price changes, suggesting that the corporate bond market serves an important role in the price discovery process. The fact that some bond traders posses superior information related to the value of corporate bonds, and hence might take advantage of this private information at the expense of uninformed traders suggests that bond holders require compensation for bearing the asymmetric information risk. Using a transaction-based asymmetric information measure (AIM) for individual corporate bonds, I find that yield spreads of high-yield corporate bonds are significantly affected by changes in the degree of information asymmetry, even

[30] The Wall Street Journal, 10/31/2001.
[31] See speech by former SEC Chairman Arthur Levitt: "The Importance of Transparency in America's Debt Market", at the Media Studies Center, New York, N.Y., on September 9th, 1998.

after accounting for effects of liquidity and other traditional corporate bond pricing factors. A one-standard-deviation jump in the AIM measure of a corporate bond causes the bond's yield spread to increase by 71 basis points. Furthermore, the AIM measure itself explains about 10% of the changes in yield spreads. The strong evidence of information and liquidity components in the corporate yield spreads provides insight into the credit spread puzzle.

The rest of the paper is structured as follows. Section 2.1 describes the AIM measure, which is derived from an asymmetric information asset pricing model, followed by empirical specifications of this measure for corporate bonds. Section 2.2 describes the data used for this study with special emphasis on corporate bond transaction data from the NASD's TRACE system. Section 2.3 contains summary descriptions of the results from estimating the private information content of individual corporate bonds. In section 2.4, I empirically test whether corporate yield spreads are related to the level of asymmetric information and liquidity of individual bonds. Various robustness checks are performed in section 2.5. I conclude my arguments in section 2.6.

The Asymmetric Information Measure and its Empirical Specifications for Corporate Bonds

Private information content of common stocks has been of extreme interest to both academics and financial practitioners, and several approaches have been suggested for its measurement. These approaches could be classified into two categories: informal measures and formal microstructure model based measures. Informal asymmetric information measures include measures related to financial analysts, such as the forest error or the forecast dispersion [Krishnaswami and Subramaniam (1998), Gilson et al. (1998), D' Mello and Ferris (2000)], and the number of following financial analysts [Brennan and Hughes (1991), Brennan et al. (1993), Elton, Gruber and Gultekin (1984)], the market-to-book ratio or the price earning ratio [Smith and Watts (1992), McLaughlin et. al. (1998)], and the firm-specific return variation [Bhagat et al. (1985), Blackwell et al. (1990), Clark and Shastri (2001), Van Ness et al. (2001). However, empirical studies show that these informal measures present significant drawbacks. For example, Easley, O'Hara and Paperman (1998) examine the relationship between analyst coverage and their PIN (probability of informed trading) measure. They find that the number of financial analysts is not a good proxy for information-based trading. Similar conclusions are reached by Chung et al. (1995), Clarke and Shastri (2001) and Van Ness et al. (2002). Clarke and Shastri (2001) and Van Ness et al. (2001) also cast some doubts on using the market-to-book ratio or the price earning ratio to measure private information as they find that these two measures have non-significant and sometimes even negative, correlations with several alternative information asymmetry measures. Similarly, using the firm-specific return variation as a proxy for the degree of information-based trading is also very controversial. Morck et al. (2000) and Drunev (2004) argue high specific return variations are often related to a more informative price. Hence the correlation between return variations and the degree of private information is negative, inconsistent with the argument that firms with high return variations tend to be more risky, less known by the market and the degree of private information is higher.

A second group of measures are derived from theoretical microstructure models, which include the informational component of bid-ask spreads and the PIN. As other informal measures, they have also received various critics from the financial literature.

O’Hara (1995) declares that it is difficult to distinguish between the transitory and informational component of the bid-ask spread. This argument has been supported by several empirical studies. The estimated information components range from about 10% of the total bid-ask spread [George et al (1991)] up to 40% [Madhavan (1997)]. Neal and Wheatley (1998) and Van Ness et al. (2001) concludes that the informational component of spreads is rather a noisy transformation of the total bid-ask spread and hence, these microstructure measures are poorly specified for measuring a security’s degree of information asymmetry.

Another widely accepted formal measure is the PIN measure, which is proposed and extended in a series of theoretical and empirical papers by Easley and O’Hara and their coauthors. They show that the PIN measure has significant effects on stock returns and its effects dominate those of other traditional factors. This measure has received extensive support since its publication. It has been shown to be strongly related to the specific stock return variations [Durnev et al. (2004)], the bid-ask spread [Chung and Li (2003)] and the cost of capital [Botosan and Plumlee (2003)]. However, due to data limitations, estimating the PIN for corporate bonds turns out to be extremely difficult.

This paper employs an alternative approach which measures information asymmetry from transaction data, instead of quotes data. Burlacu et al (2005) is the first to apply this approach in the equity securities. Using CRSP US daily stock data for about 7,000 stocks over 17 years, they find that this AIM measure has a strong impact on stock returns and dominates traditional asset pricing factors such as β and the Fama and French factors.

The AIM measure is obtained directly from a Rational Expectations (RE) model with multiple securities and many sources of uncertainty. This model is essentially a generalization of the Grossman and Stiglitz (1980) model, which focuses on an economy where some investors are more informed on the future distributions of a security's returns than others. Intuitively, if the market is noisy, price of a security contains some private information about future returns. Since this part of private information is not revealed by prices, it is related to future returns. The AIM measure employed in this paper basically uses the degree of correlation between current security prices and future returns as a measure of the private information embedded in the security.

The Model

Consider an economy with information asymmetry. Investors trade *N* risky securities and one risk-free security at time *0*, and consume at time *1* when these securities pay off. The pay-off (liquidation value) of risky security *i* is generated by one specific and *K* common factors as follows:

(2.1) $p_i^1 = \mu_i + \sum_{k=1}^{K} \beta_{i,k}\theta_k + \varepsilon_i$,

where p_i^1 is the payoff of risky security i, μ_i and θ_k represent the specific and common factors respectively, $\beta_{i,k}$ denotes the factor loading to the common factor k for security *i*, and ε_i is the error term. The realization of the specific and common factors is known to λ percent of the investors, known as informed traders, at time *0*, while the remaining investors only know that these factors are independent random variables and have normal distributions. Investors are constant absolute risk averse, and they trade to maximize their utility at time *1*:

$$(2.2)\ U\left(I_j^1\right) = -e^{-\alpha I_j^1},$$

where I_j^1 is investor *j*'s income at time *1*, and α denotes the risk aversion coefficient for investor *j*. The per capita supply of security *i* is assumed to be an independent random variable z_i, which is normally distributed. The supply z_i is unknown by both the informed and uninformed investors.

For expositional convenience, I drop the subscript for each random variable and obtain random vectors. Specifically, let

$$(2.3)\ P = \begin{bmatrix} p_1 & p_2 & p_3 & \ldots & p_N \end{bmatrix}',$$

$$(2.4)\ \mathrm{B} = \left[\begin{array}{cccc|cccc} 1 & 0 & \ldots & 0 & \beta_{11} & \beta_{12} & \ldots & \beta_{1K} \\ 0 & 1 & \ldots & 0 & \beta_{21} & \beta_{22} & \ldots & \beta_{2K} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \ldots & 1 & \beta_{N1} & \beta_{N2} & \ldots & \beta_{NK} \end{array}\right],$$

$$(2.5)\ \Theta = \begin{bmatrix} \mu_1 & \mu_2 & \ldots & \mu_N & \theta_1 & \theta_2 & \ldots & \theta_K \end{bmatrix}',$$

$$(2.6)\ \mathrm{E} = \begin{bmatrix} \varepsilon_1 & \varepsilon_2 & \varepsilon_3 & \ldots & \varepsilon_N \end{bmatrix}',$$

$$(2.7)\ \text{and}\ Z = \begin{bmatrix} z_1 & z_2 & z_3 & \ldots & z_N \end{bmatrix}'.$$

Thus, the *N*-vector of securities' payoff at time *1* thus can be written as

$$(2.8)\ P^1 = B\Theta + E,$$

where Θ is the (N+K) dimensional vector containing both N common factors and K specific factors, and B is the (N, N+K) block matrix obtained by joining the N dimensional identity matrix with the matrix of asset factor loadings. Without loss of generality, it is assumed the expected values and variance-covariance matrices for Θ, E and Z are $\overline{\Theta}$, 0, $\overline{Z}$, and Ω_{Θ}, Ω_{ε} and Ω_{z}, respectively. All variance-covariance matrices are further assumed to be regular.

Under certain regularity conditions, it is not difficulty to show that when some investors possess superior information about future price movements, there exists a unique equilibrium in which current equilibrium securities prices are linear functions of the informed investors' private information Θ and asset supplies Z at time *1*:

(2.9) $P^{0} = A_{0} + A_{1}\Theta - A_{2}Z$

where A_{0}, A_{1}, A_{2} are the coefficient matrices. Since the supplies Z are unknown to both informed and uninformed investors, the uninformed investors are not able to infer the realization of Θ from current securities prices. Therefore, part of the private information remains in the hands of informed investors. Since $P^{1} = B\Theta + E$, the equilibrium price at time *0* also suggests that the total amount of uncertainty about future price movements, measured by $\mathrm{var}\left(P^{1} - P^{0}\right)$, is determined by uncertainty related to pricing factors (Ω_{Θ}), pricing noise (Ω_{ε}) and per capita asset supply (Ω_{z}). As part of informed traders' private information is incorporated into prices through trading, observing current security prices helps to reduce the uncertainty about future price changes to $\mathrm{var}\left(P^{1} - P^{0} \middle| P^{0}\right)$, which is determined by the remaining uncertainty about the pricing factors after prices are known to the market ($\Omega_{\Theta|P^{0}}$), and Ω_{ε} and Ω_{z}. Therefore, the drop in the volatility in future price changes from $\mathrm{var}\left(P^{1} - P^{0}\right)$ to

$\mathrm{var}\left(P^1 - P^0 \middle| P^0\right)$ is solely attributed to the reduction from Ω_Θ to $\Omega_{\Theta|P^0}$, which, in turn, is caused by the information asymmetry between information and uninformed traders. Since more aggressive trading on private information results in more information revealed by prices, and hence smaller uncertainty about future price movements, the difference between Ω_Θ and $\Omega_{\Theta|P^0}$ could be used to suggest a measure for the degree of information asymmetry during the trading process. Specifically, the degree of information asymmetry for security *i* at time *0* is defined as the amount of private information that is *unrevealed* by current prices of all existing securities ($\Omega_{\Theta|P^0}$), relative to the total amount of initial private information (Ω_Θ). As the difference between Ω_Θ and $\Omega_{\Theta|P^0}$ can not be directly estimated from market data, I used the difference between $\mathrm{var}\left(P^1 - P^0\right)$ and $\mathrm{var}\left(P^1 - P^0 \middle| P^0\right)$ as a proxy for information asymmetry. The amount of unrevealed private information can be calculated as $Var(P_1^i - P_0^i) - Var(P_1^i - P_0^i | P_0)$, while the total amount of initial private information can be estimated by $Var(P_1^i - P_0^i)$. Therefore, the asymmetric information measure for security *i* can be expressed a

$$(2.10)\ AIM^i = 1 - \frac{Var(P_1^i - P_0^i | P_0)}{Var(P_1^i - P_0^i)}.$$

The idea behind this method is quite straightforward. In an economy where everyone possesses the same information about security *i* and the information is processed in the same way, in equilibrium, security prices contain no further information about future price movements. As a result, current security price levels are not correlated with future price changes, and hence are not useful in reducing associated uncertainties, i.e., $Var(P_1^i - P_0^i | P_0) = Var(P_1^i - P_0^i)$ and $AIM^i = 0$. Conversely, in an economy with information asymmetry, part of the information about future price movements remain in the possession of informed traders. Since this private information is not revealed by prices, it conditions future price movements. Consequently, future security price changes will be dependent on current price levels. Therefore, current security prices are helpful in reducing uncertainties about future price changes, i.e. $Var(P_1^i - P_0^i | P_0) <$ $Var(P_1^i - P_0^i)$ and $AIM^i > 0$. Furthermore, the degree of dependence of future price changes on current price levels serves as a valuable measure of the amount of private information embedded in security prices. The more private information remains in the hands of informed traders, the smaller the conditional variance of future price changes and the higher the difference between $Var(P_1^i - P_0^i)$ and $Var(P_1^i - P_0^i | P_0)$, and, hence the higher the AIM^i.

Empirical Specifications

To implement this method in the corporate bond market, notice that the AIM measure is obtained by projecting one-period bond price changes on price levels at the beginning of the corresponding period. The resulting R^2 from this regression is exactly the AIM derived from the RE model. Specifically, following Burlacu et al (2005), I use the next regression for the AIM estimation:

(2.11) $\Delta P_t^i = \alpha^i + \sum_{j=1}^{N} \beta^{i,j} P_{t-1}^j + \varepsilon_t^i$,

where P_{t-1}^i denotes the price of bond *i* at the beginning of period *t* and

(2.12) $\Delta P_t^i = P_t^i - P_{t-1}^i$,

represents bond *i*'s price changes during period *t*. I take logarithms of corporate bond prices before I calculate price changes, since the logarithms of prices are closer to the normality hypothesis. Furthermore, to ameliorate the econometric properties of the AIM, which is bounded in the [0,1] interval, I apply the following transformation to the original R^2 to get the new AIM for bond *i*:

$$(2.13)\ AIM^{i} = \ln\left(\frac{R_i^2}{1-R_i^2}\right).$$

In order to complete the empirical specification of the AIM, a decision needs to be made on what prices should be included in the above regression for a relevant extraction of information about future bond price movements. Theoretically, in a world where values of all securities are more or less related to each other, price changes of any bond *i* should be projected on the prices of all securities to get a full estimation of the AIM. This approach unfortunately is unfeasible in practice. Limited observations on corporate bonds preclude the use of a large number of securities as regressors. Therefore, this study includes a few related securities and a market index that have been suggested in the literature as important information sources for individual corporate bond price changes.

Specifically, the information sources include the price of bond *i*, the price of the issuer's common stock, the price of a corresponding default-free bond whose future cash flows perfectly match those of the target corporate bond, and the S&P 500 index level. The rationale behind using the stock price as an information source is fairly simple. As a firm's stock and bonds represent claims to the same underlying assets, information regarding the value of the assets will affect both the firm's stock and bonds. Hence, if information-based trading takes place in the stock market, stock prices contain valuable information about future bond price movements. Empirical evidence of the predictive power of stock price on future bond price changes has been documented in both Kwan (1996) and Zhou (2005a). Besides individual stock prices, I also include the S&P 500 index level to provide information about overall stock market conditions. Previous studies [see for example, Blume, Keim and Patel (1991) and Cornell and Green (1991)] have shown that high-yield corporate bonds are very sensitive to stock market movements. Finally, the price of a corresponding default-free bond with matching future cash flows is included to control for interest rate risk. The price of default-free bonds is obtained by discounting the cash flows of the corresponding corporate bond at default-free zero-coupon interest rates. These zero-coupon rates are estimated by employing a modified version of the extended Nelson-Siegel model [Bliss (1997)] on the observed on-the-run Treasury curve.[32]

To test the robustness of my results, I propose several specifications for the AIM by increasing the number of information sources in the regression. In the simplest specification, besides the price of the target corporate bond, I include the price of the issuer's common stock to capture firm-specific information gleaned from the issuer's equity security:

$$(2.14)\quad \Delta P_t^i = \alpha^i + \beta^{i,b} P_{t-1}^i + \beta^{i,s} S_{t-1}^i + \varepsilon_t^i,$$

with P and S denoting the price of the target bond and its corresponding common stock respectively. To enrich the extraction of information related to corporate bond price changes, I also consider the information provided by market movements:

$$(2.15)\quad \Delta P_t^i = \alpha^i + \beta^{i,b} P_{t-1}^i + \beta^{i,s} S_{t-1}^i + \beta^{i,m} M_{t-1}^i + \varepsilon_t^i,$$

[32] See Appendix B for a description of the extend Nelson-Siegel model and related estimation details.

with M representing the S&P 500 index level. Furthermore, as the price of corresponding default-free bonds contains information about risk-free rate changes, this variable is also added to the model, and hence the last specification for the AIM used in this study becomes:

$$(2.16)\quad \Delta P_t^i = \alpha^i + \beta^{i,b} P_{t-1}^i + \beta^{i,df} DF_{t-1}^i + \beta^{i,m} M_{t-1}^i + \beta^{i,s} S_{t-1}^i + \varepsilon_t^i ,$$

where DF stands for default-free bond.

Data Description

Compared to the abundant literature on the pricing of equity securities, research on the price behavior of corporate bonds is much sparser due to the lack of high quality bond data.[33] Unlike stocks, the majority of corporate bond transactions take place on the OTC market[34] and no price related information had been available to the public until NASD introduced the Fixed Income Pricing System (FIPS)[35] in 1994, which was later incorporated into a broader system known as TRACE[36] on July 1st, 2002. Under TRACE rules,[37] all NASD members are obligated to submit transaction reports for any secondary market transaction in TRACE-eligible securities[38] between 8:00PM and

[33] The omission of research in this important market has been noted by Goodhart and O'Hara (1997) in an extensive review of the market microstructure literature.
34 Some corporate bonds are also traded on the NYSE's Automated Bond System (ABS). But the trading volume is relatively low compared to that on the OTC market.
35 For more information about FIPS, please see the NASD Notice to Members (NtM) 94-23, Alexander, Edwards, and Ferri (1999, 2000), and Hotchkiss and Ronen (2002).
[36] Zhou (2005a) provides a brief review of recent developments in the corporate bond market, as well as a detailed description of the TRACE system.
37 Also known as the NASD Rule 6200 series.
38 According to NASD Rule 6210(a), TRACE-eligible securities 'mean all United States dollar denominated debt securities that are depository eligible securities under Rule 11310(d); Investment Grade or Non-Investment Grade; issued by United States and/or foreign private issuers; and: (1) registered under the Securities Act of 1933 and purchased or sold pursuant to Rule 144A of the

6:30PM (EST) within one hour and fifteen minutes of the time of execution.[39] Based on these submitted trading reports, NASD immediately distributes to the market transaction information on investment grade bonds with $1 billion or higher initial issuance, as well as a set of 50 most actively traded Non-Investment grade bonds (TRACE 50 thereafter). In the subsequent two and a half years, more and more corporate bonds have been designated for immediate dissemination, and beginning February 7th, 2005, NASD has begun to fully disseminate transaction information on virtually all corporate bonds in real-time.

Since high-yield bonds incorporate an equity component and are more sensitive to firm-specific information than investment grade bonds, transaction data for the TRACE 50 bonds are used to study whether information is priced in corporate bonds. Based on the same data set, Zhou (2005a) finds that current corporate bond prices contain valuable information about future stock price movements, identifying an important informational role for the corporate bond market. The evidence of information-based trading in the corporate bond market provides encouragement for continued exploration of whether information risk is priced in the corporate bond market.

Specifically, this data set contains execution date and time (recorded to the second), price, yield, quantity (and other information that can be used to purge invalid transaction reports) for every trade in the TRACE 50 high-yield bonds during the period from July 1st, 2002 to September 30th, 2004[40]. The TRACE 50 bonds are

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Securities Act of 1933.' It does not include debt securities issued by government-sponsored entities (GSE), mortgage-backed or asset-backed securities, collateralized mortgage obligations and money market instruments.

[39] The reporting time has been shortened to 15 minutes as of July 1st, 2005.

[40] On October 1st, 2004, NASD began its second stage dissemination, and many more high-yield bonds are subject to dissemination. The concept of TRACE 50 does not exist any more.

chosen by the NASD advisory committee based on criteria such as the security's volume, price, name recognition, amount of research attracted, amount outstanding, number of dealers that are making a market in this security and the security's contribution to the TRACE 50's industry diversity. Similar to the FIPS 50 bonds studied by Hotchkiss and Ronen (2002), the TRACE 50 bonds are characterized by high trading volume, both in terms of number of transactions and number of block size trades, and similar trading patterns to the issuer's stock. Over time, bonds with small trading volume have been replaced with more active bonds. Transaction information on the first TRACE 50 bonds has been released to the market on a real-time basis since July 1st, 2002. From July 13th, 2003 until September 30th, 2004, the TRACE 50 list was updated every 3 months. During this time period, 177 high-yield bonds from 135 issuing firms were included in the TRACE 50 lists for dissemination.

More frequent updating of the TRACE 50 lists since July 13th, 2003 makes it difficult to keep track of the time-series variation of liquidity and information asymmetry of any individual bond. To mitigate the effects introduced by discontinued dissemination for some bonds, I focus on the first TRACE 50 list which covers the period from July 1st, 2002 to July 13th, 2003, a total of 259 trading days. For each individual bond in this list, daily close price data are constructed by keeping the transaction price for the last valid trade before 6:30PM (EST), the time when TRACE is closed. Daily stock price data for the issuing firms is retrieved from CRSP for this time period. Since some firms are not public, and some are traded on the OTC market or the pink sheet market, corresponding stock price data does not exist for 7 of these bonds. Among the remaining 43 bonds, 8 are issued by firms with very inactive stocks, which do not have valid end of day bid-ask quotes or close prices for some of the trading days. By excluding these firms from my sample, I am left with a panel of

36 bonds across 259 trading days.

Table 2.1 contains summary characteristics for the 36 corporate bonds and their issuing firms. Issuing firms are fairly large, with median total asset value of 8744 million USD, and characterized by high financial leverage, which is consistent with the low credit ratings of these bonds. All 36 bonds in the sample are non-convertible, with 14 (38.89%) being callable prior to maturity. The bonds included in this study represent 6 different industries, concentrated in Manufacturing (30.56%), Service (30.56%) and Telecommunications (22.22%). More than half of the 36 bonds are senior unsecured notes. Coupon payments are made twice per year for each of the 36 bonds, and all are fixed plain-vanilla coupons, except for one bond which has a variable coupon size. The average coupon rate is 8.848%. During the one year period studied by this paper, over 80% of the 36 TRACE 50 bonds were rated between CCC and BB by S&P and none of them defaulted.

Table 2.1: Characteristics of 36 TRACE 50 Bonds and Their Issuing Firms

Panel 1:

Variable	Mean	Median	Min	Max	Std Dev
Issuer’s Total Assets ($ millions)	12642.4	8744	2265.9	36566	9364.9
Leverage (Total Liabilities/Total Assets)	0.8529	0.8667	0.5024	1.1835	0.1196
Coupon Rate	8.8483	9.0625	6.0000	11.6250	1.2945
Time to Maturity (year)	6.8998	6.6283	2.5435	26.7050	3.7830

Panel 2:

Bond Type	SRDEB	SRNT	SRSECNT	SRSUBNT	SRUNNT	UNNT
Number of Bonds	1	7	2	6	19	1
Percentage	2.78	19.44	5.56	16.67	52.78	2.78

Table 2.1(Continued)

Panel 3:

S&P Rating	BBB	BB	B	CCC	CC	C	NR
Number of Bonds	3	10	14	5	1	1	2
Percentage	8.33	27.78	38.89	13.90	2.78	2.78	5.56

Panel 4:

Coupon Type	Variable	Plain Vanilla Fixed Coupon
Number of Bonds	1	35
Percentage	2.78	97.22

Panel 5:

Payment Frequency	Semiannually
Number of Bonds	36
Percentage	100

Panel 6:

Industry	ENGY	FIN	MANU	SERV	TELE	TRANS
Number of Bonds	4	1	11	11	8	1
Percentage	11.11	2.78	30.56	30.56	22.22	2.78

Panel 7:

Callable	Yes	No
Number of Bonds	14	22
Percentage	38.89	61.11

Panel 8:

Convertible	Yes	No
Number of Bonds	0	36
Percentage	0	100

This table contains summary characteristics for the 36 corporate bonds and their issuing firms at the time of their initial entry to the TRACE 50 list. Firm characteristics are based on data from COMPUSTAT, while bond characteristics are determined from the TRACE 50 dataset. Most of these descriptive bond data were obtained from NASD, with the remainder provided by the issuing firms. The following abbreviations are used in this table: for bond type, SRDEB (Senior Debenture), SRNT

(Senior Note), SRSECNT (Senior Secured Note), SRSUBNT (Senior Subordinated Note), SRUNNT (Senior Unsecured Note), and UNNT (Unsecured Note); for industry, ENGY (Energy), FIN (Financial), MANU (Manufacturing), SERV (Services), TELE (Telecommunications) and TRANS (Transportation).

Finally, in order to measure the private information content of individual bonds, and calculate the yield spread of a corporate bond (which is defined as the difference between the corporate bond yield and the yield on a default-free bond with exactly the same maturity and coupon size), I first estimate the term structure of risk-free zero-coupon interest rates. I use data on the most recently issued 3-month, 6-month US Treasury bills, 1-year Treasury note, as well as US Treasury bonds with maturities closest to 2, 3, 5, 7, 10 and 30 years from CRSP Daily US Treasury files. The extended Nelson-Siegel model [Bliss (1997)] is employed for estimation.

Measuring liquidity and the Private Information Content of Individual Corporate Bonds

Trading volume has been a widely cited measure for liquidity as more active markets tend to be more liquid [see for example, Chordia, Roll and Subrahmanyam (2000) and Hasbrouck (2003)]. Unfortunately, data for daily bond volume in each individual bond is not easy to construct from the TRACE 50 transaction dataset since the exact size of a trade is disseminated only for those trades whose par values do not exceed 1 million US dollars. For block size trades, only a sign of '1MM+' is recorded. As an alternative, I use trading frequency, which is equal to the number of total valid transactions per day (NOT), as a proxy for liquidity. This measure is consistent with notion that liquid bonds tend to be traded more frequently. I also use the trading impact on bond yields as a measure of illiquidity (ILLQ):

$$(2.17)\ ILLQ_{j,t} = \frac{\left|\log(ys_{j,t}) - \log(ys_{j,t-1})\right|}{volume_{j,t}},$$

where ys stands for yield spread.

While liquidity is easy to measure from the data, estimating private information content involves applying the empirical models proposed in section I to time series data for each bond individually. Specifically, for each bond, I estimate the regressions for 3 different AIM specifications with a sample of 10 weeks, which represents 50 observations. The resulting AIM represents the private information content of the bond during this period. The 10-week periods are then moved day by day, and regressions (2.14)-(2.16) are estimated accordingly. This allows us to rapidly capture changes in the information flow and determine bond specific AIM for every single day on the sample period. Therefore, AIM measures are available for each trading day in the sample period from September 11th, 2002 to July 11th, 2004 for each of the 35 TRACE 50 bonds. Summary statistics for these AIM measures, as well as the liquidity measures NOT and ILLQ are provided in Table 2.2.

Panel 1 presents some interesting results. First, compared to the stock market or the Treasury bond market, low grade corporate bonds are much less frequently traded, with a median trade number of 2 per day during the sample period. Secondly, the group of low grade corporate bonds studied in this paper contains significantly higher private information during the period from July 1st, 2002 to July 11th, 2003 than the 6988 common stocks examined by Burlacu et al (2005) from January 1st, 1985 to December 31st, 2002. Information extracted from prices of the target corporate bond

Table 2.2 Descriptive Statistics for Liquidity Measure, the AIM measures and their Cross Correlations

Panel 1

	Mean	Median	Min	First Quartile	Third Quartile	Max	Standard Deviation
NOT	2.36	2	0	0	3	15	2.34
ILLQ	6.732	3.129	0	2.046	7.118	38.214	5.396
AIM1	0.215	0.196	0.000	0.117	0.304	0.855	0.127
AIM2	0.255	0.242	0.002	0.093	0.350	0.875	0.127
AIM3	0.291	0.288	0.003	0.192	0.382	0.876	0.125
LOGAIM1	-1.778	-1.628	-9.114	-2.143	-1.190	-0.157	0.820
LOGAIM2	-1.534	-1.418	-6.492	-1.843	-1.050	-0.133	0.659
LOGAIM3	-1.348	-1.244	-5.936	-1.650	-0.962	-0.133	0.524

Panel 2:

	AIM1	AIM2	AIM3	LOG-AIM1	LOG-AIM2	LOG-AIM3	NOT	ILLQ
AIM1	1.000	0.935	0.878	0.882	0.835	0.808	-0.029	0.109
AIM2	0.935	1.000	0.935	0.834	0.911	0.874	-0.027	0.213
AIM3	0.878	0.935	1.000	0.787	0.852	0.943	0.001	0.117
LOGAIM1	0.930	0.839	0.753	1.000	0.902	0.829	-0.041	0.121
LOGAIM2	0.882	0.834	0.787	0.902	1.000	0.910	-0.046	0.180
LOGAIM3	0.808	0.874	0.943	0.829	0.910	1.000	-0.020	0.229
NOT	-0.029	-0.027	0.001	-0.041	-0.046	-0.020	1.000	-0.189
ILLQ	0.109	0.213	0.187	0.072	0.180	0.139	-0.189	1.000

Panel 3:

	AIM1	AIM2	AIM3	LOGAIM1	LOGAIM2	LOGAIM3	NOT	ILLQ
AIM1	1.000	0.900	0.816	0.930	0.848	0.789	-0.086	0.143
AIM2	0.900	1.000	0.905	0.839	0.953	0.883	-0.085	0.193
AIM3	0.816	0.905	1.000	0.753	0.855	0.969	-0.064	0.154
LOGAIM1	0.930	0.839	0.753	1.000	0.876	0.779	-0.089	1.120
LOGAIM2	0.848	0.953	0.855	0.876	1.000	0.889	-0.085	1.108
LOGAIM3	0.789	0.883	0.969	0.779	0.889	1.000	-0.071	0.149
NOT	-0.086	-0.085	-0.064	-0.089	-0.085	-0.071	1.000	-0.217
ILLQ	0.143	0.193	0.154	0.120	0.108	0.149	-0.217	1.000

Panel 1 presents the mean, the median, the minimum, the maximum, the first quartile, the third quartile, and the standard deviation for the liquidity measures: number of transactions (NOT), and Amihud's illiquidity measure (ILLQ), and the AIM measures. AIM1, AIM2 and AIM3 correspond to specifications (2.14)-(2.16) respectively. LOGAIM1, LOGAIM2 and LOGAIM3 are obtained by performing the transformation (2.13) on AIM1 through AIM3. Panel 2 and 3 contain cross-correlation coefficients between the liquidity measures and various AIM measures. Panel 2 has the coefficients based on the pooled data while Panel 3 includes the cross-sectional averages across the 35 bonds of correlations over time.

and its issuer's common stock reduces the uncertainty about future bond price movements of about 19.6%, compared to a maximum of about 7% from the different AIM specifications for common stocks by Burlacu et al (2005). Including the S&P 500 index level as one of the information sources helps to further reduce the uncertainty by 4.6%, and the addition of the price of corresponding default-free bond makes it possible to explain 28.8% of future bond prices changes. Finally, the overall dispersion of my AIM measures for corporate bonds is much higher than that for common stocks, with an average standard deviation of about 12.7% for bonds, versus 4% for stocks. The majority part of this variation can be explained by the fact that my AIM measures for corporate bonds display a high variability in time. The average time-series standard deviation is about 10.2%, with little deviation across different measures. This result differs from Easley, Hvidkjaer and O'Hara (2002) who find that the estimated PIN is very stable across time. AIM measures in this paper thus raise the hope of keeping a closer track of the dynamics in information flow and capturing the changes in private information rapidly.

An interesting question is how these AIM measures are related to the liquidity measure, both across bonds and over time. According to market microstructure theory, liquidity is an inter-temporal concept which is not necessarily related to how information gets incorporated into prices.[41] Empirical microstructure work, however, has shown that infrequently traded stocks are generally illiquid and have high private information content [see for example, Easley, Kiefer, O'Hara and Paperman (1996), Chordia, Subrahmanyam and Anshuman (2001), Easley, Hvidkjaer and O'Hara (2002) and Burlacu, Fontaine and Jimenez-Garces (2005)]. If actively traded stocks face a less severe adverse selection problem due to information-based trading, the negative correlation found in these studies should not be surprising.

Panel 2 and 3 in Table 2.2 present the correlation coefficients between trade frequency and various AIM estimates for corporate bonds. Except for the correlation between NOT and AIM3, all of the correlations are highly significant and exhibit the anticipated signs. Trade frequency is negatively correlated with the degree of information asymmetry, with the correlation coefficient varying from -0.020 to -0.046. Illiquidity measure (ILLQ) is negatively correlated with NOT, and positively correlated with the AIM measures. The magnitude of correlation for the set of low grade corporate bonds is smaller than that for common stocks found in other studies. For example, Easley, Hvidkjaer and O'Hara (2002) find the average correlation between their PIN estimates and the logarithm of average daily trading volume is -0.58, fluctuating between -0.38 and -0.71. Burlacu et al (2005) obtain a much smaller estimate of the correlation with a range of -0.04 to -0.10, which is still greater than

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[41] A strand of microstructure literature has been focused on the notion of liquidity. See for example, Demsetz (1968), Garman (1976), Stoll (1978), Ho and Stoll (1981), Amidhud and Mendelson (1986, 1988), O'Hara and Oldfield (1986), Grossman and Miller (1988), Biais (1993) and Madhavan and Smidt (1993). O'Hara (1995) provides an excellent textbook treatment of liquidity issues in microstructure theory. For a clear illustration of the difference between liquidity and price discovery, see O'Hara (2003).

those for corporate bonds. Corporate bond trade frequency, however, displays a stronger correlation with AIM estimates over time. Panel 3 shows that cross-sectional averages of correlations over time vary from -0.064 to -0.086. Finally, not surprisingly, different AIM measures for the bonds exhibit strong positive correlations with a minimum coefficient of 0.808.

Information Asymmetry, Liquidity and Corporate Yield Spreads: Benchmark Results

With the private information content and liquidity of individual bonds estimated above, this section takes the next step and studies whether these factors possess explanatory power for corporate yield spreads, in addition to those from the traditional corporate bond pricing models. During the sample period examined in this paper, the corporate bond market experienced a major increase in transparency when NASD started its Phase II implementation of public corporate bond transaction reporting through the TRACE system on March 3rd, 2003[42]. The pool of corporate bonds which are subject to immediate dissemination was dramatically expanded from 500 to 4,200. The enhanced transparency of the corporate bond market could cause significant changes for the key variables studied in this paper, including informational efficiency, liquidity and yield spreads of the 35 TRACE 50 bonds. Therefore, I divide my sample into two parts, one before the end of February of 2003 (period I) and one after (period II). Figure 2.1 and Figure 2.2 depict how the main variables change over time, and summary statistics for these variables are reported in Table 2.3.

[42] The plan for Phase II dissemination of public corporate bond transaction reporting through NASD's Trade Reporting and Compliance Engine (TRACE) was approved by SEC and publicly announced on February 28th, 2003. See NASD News Release on February 28th, 2003.

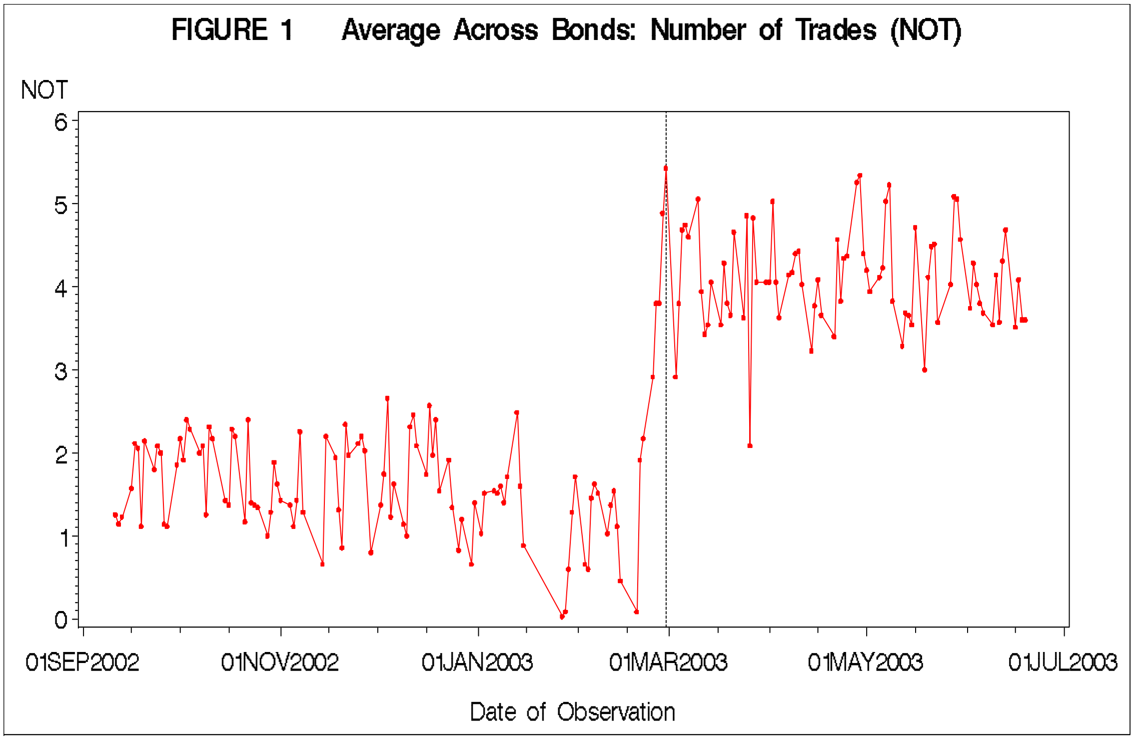


Figure 2.1 Time-Varying Liquidity

This figure plots the cross-sectional average of the daily time series of number of trades (NOT) for the 35 TRACE 50 corporate bonds. The vertical dashed line refers to the day February 28th, 2003, when news about the SEC's approval of NASD's phase II implementation of public corporate bond transaction reporting through the TRACE system on March 3rd, 2003 became available to the market. During the Phase II dissemination, the pool of corporate bonds which are subject to immediate dissemination was dramatically expanded from 500 to 4,200. The data set consists of 184 daily observations, from September 11th, 2002 to June 19th, 2003.

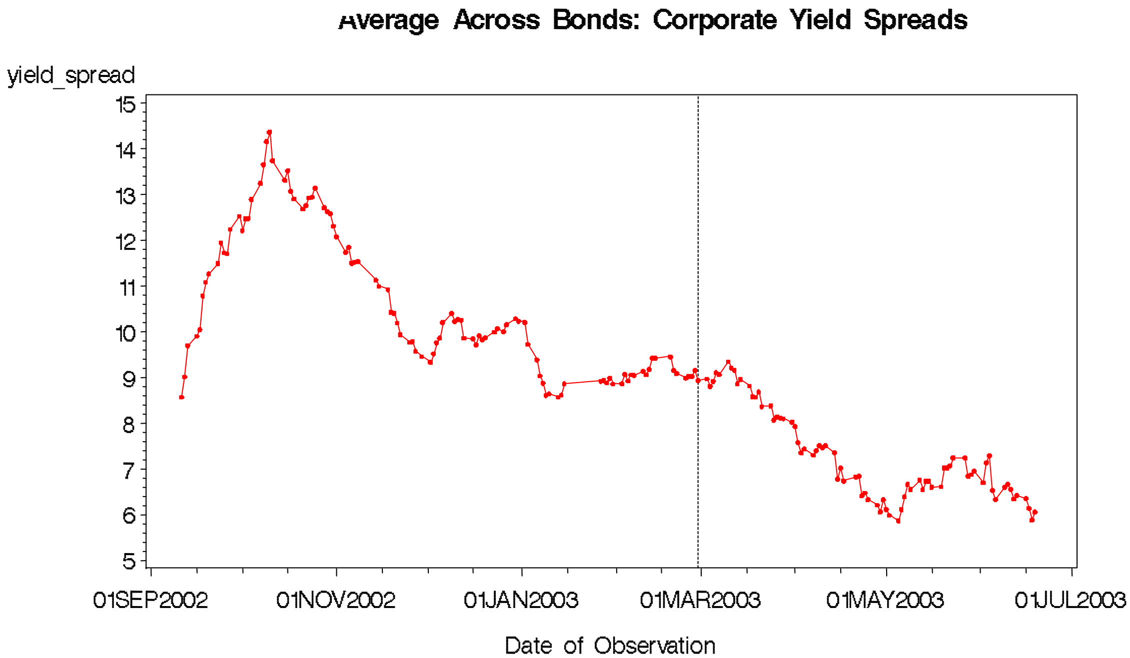


Figure 2.2 Time-Varying Corporate Yield Spreads

This figure plots the cross-sectional average of the daily time series of Corporate Yield Spreads for the 35 TRACE 50 corporate bonds. Yield spread is calculated as the difference between the corporate bond yield and the yield on a default-free bond with exactly the same maturity and coupon size. Yield on the corresponding default-free bond is estimated by employing a modified version of the extended Nelson-Siegel model [Bliss (1997)] on the observed on-the-run Treasury curve. The vertical dashed line refers to the day February 28th, 2003, when news about the SEC's approval of NASD's phase II implementation of public corporate bond transaction reporting through the TRACE system on March 3rd, 2003 became available to the market. During the Phase II dissemination, the pool of corporate bonds which are subject to immediate dissemination was dramatically expanded from 500 to 4,200. The data set consists of 184 daily observations, from September 11th, 2002 to June 19th, 2003.

Table 2.3: Sub-Sample Summary Statistics for Corporate Yield Spread, Liquidity and AIM Measures

Panel 1: Mean and Time-Series Standard Deviations

Variable	Period I Mean	TS Std. Dev.	Period II Mean	TS Std. Dev.
YS	10.562	2.274	7.272	1.352
NOT	1.681	1.315	4.090	2.197
ILLQ	7.476	6.778	3.289	4.237
LOGAIM1	-1.778	0.548	-1.834	0.574
LOGAIM2	-1.525	0.414	-1.864	0.503
LOGAIM3	-1.365	0.341	-1.388	0.395

Panel 2: Time-Series Correlation with Yield Spreads

	NOT	ILLQ	LOGAIM1	LOGAIM2	LOGAIM3
YS	*0.035*	0.107	0.325	0.316	0.283

This table reports summary statistics for YS (Yield Spread), NOT (Number of Trades), ILLQ (Amihud's Illiquidity measure) and AIM measures (LOGAIM1, LOGAIM2 and LOGAIM3) for both period I (September 11th, 2002 to February 28th, 2003) and Period II (March 3rd, 2003-June 19th,2003). Yield spread is calculated as the difference between the corporate bond yield and the yield on a default-free bond with exactly the same maturity and coupon size. Yield on the corresponding default-free bond is estimated by employing a modified version of the extended Nelson-Siegel model [Bliss (1997)] on the observed on-the-run Treasury curve. AIM measures (LOGAIM1- LOGAIM3) are obtained by performing the transformation (2.13) on AIM1 through AIM3, which correspond to specifications (2.14)-(2.16) respectively. Statistics reported in Panel 1 includes the global mean of each variable (cross-sectional average of the time-series averages), the cross-sectional average of time-series standard deviation of each variable for both sub-samples. The correlations between yield spreads and the liquidity and AIM measures in time-series (averaged *across bonds) for period I is presented in Panel2. Non-significant correlations are italicized.*

First, as shown by Figure 2.1, trading activity levels for these bonds experienced a huge jump on February 28th, 2003 when news of the SEC's approval of NASD's phase II implementation of the TRACE system became available to the market, and remained high thereafter. According to Table 2.3, the average number of trades per day was 1.68 prior to March 3rd, 2003, but jumped to 4.09 afterwards. The finding that enhanced transparency in the corporate bond market increases liquidity in the already transparent TRACE 50 bonds may be due to traders becoming more aware of transparent prices. If transparency decreases transaction costs for those bonds made transparent on March 3rd and raises their liquidity, as found by Edwards, Harris and Piwowar (2005), the finding that TRACE 50 bonds also became more liquid might be due to some commonality in liquidity [see for example, Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Chordia, Sarkar and Subrahmanyam (2003)].

Second, the degree of information asymmetry in the 35 TRACE 50 bonds has been lower since the Phase II dissemination. Panel 1 of Table 2.3 shows that the average AIM estimates for period II is lower than that for period I. This result is consistent with the experimental evidence provided by Bloomfield and O'Hara (1997) that trade disclosure improves informational efficiency. However, the enhanced transparency of the bond market brings to the market some new information resources, from which extra information about future bond price movements can be extracted. It thus raises the question of whether the AIM specifications proposed in Section 1 are still appropriate in measuring the private information content of corporate bonds. Not surprisingly, the availability of additional information sources might subject my AIM measures to serious bias. This indicates that focusing on the period I sub-sample might be more appropriate.

Finally, corporate yield spreads became narrow after March 3rd (Figure 2.2). The average yield spread for the 35 bonds was 10.56% for period I. This number, however, declined by almost a third to 7.27% for period II, suggesting that the lower degree of asymmetric information from trade disclosure reduces the information risks faced by uninformed traders, and hence less compensation is required for bearing such risks. Former studies on the corporate bond yield puzzle have relied on bond data when the market is not transparent, so, to allow for comparability with these studies, and due to the possibility that larger disclosure might introduce some bias into my AIM measures as suggested above, I will focus on the period I sub-sample in the rest of this paper.

Informal Examination

This subsection conducts an informal test of whether private information content and liquidity explain corporate yield spreads. Since investors require higher yields on bonds that are less liquid to compensate for the transaction cost incurred when trading the bonds, more liquid bonds should have lower yield spreads; i.e., there should exist a negative relation between yield spreads and liquidity measures. On the other hand, the degree of information asymmetry, estimated by various AIM measures, is expected to be positively correlated with corporate yield spreads. The reason behind this positive relationship lies in the fact that during the process of price discovery, some traders possess superior information about the value of bonds, and hence might take advantage of this private information at the expense of uninformed traders. This type of informational advantage of informed traders creates a risk for uninformed traders as they constantly lose to informed ones. As a result, higher yields are required by bond holders for those bonds which possess more asymmetric information risk.

Compared to the significant cross-sectional effect of liquidity on corporate yields documented in existing literature, its time-series effects on portfolio are much smaller, as shown by Figure 2.3 and Panel 2 of Table 2.3. The correlation between NOT and yield spread is not significant, either statistically and economically, and the correlation between ILLQ and yield spread is 0.107. The degree of information asymmetry, however, is strongly correlated with corporate yield spreads. The correlations between yield spreads and the AIM measures (LOGAIM1, LOGAIM2 and LOGAIM3) are 0.325, 0.316 and 0.283, respectively, and they are all statistically significant and present the expected sign. Furthermore, Figure 2.4 shows that the AIM measures move quite closely with yield spread changes over the sample period. This significant time-series link between information asymmetry and corporate yield spreads at the portfolio reveals a promising way to better explain corporate yield spreads observed in the markets.

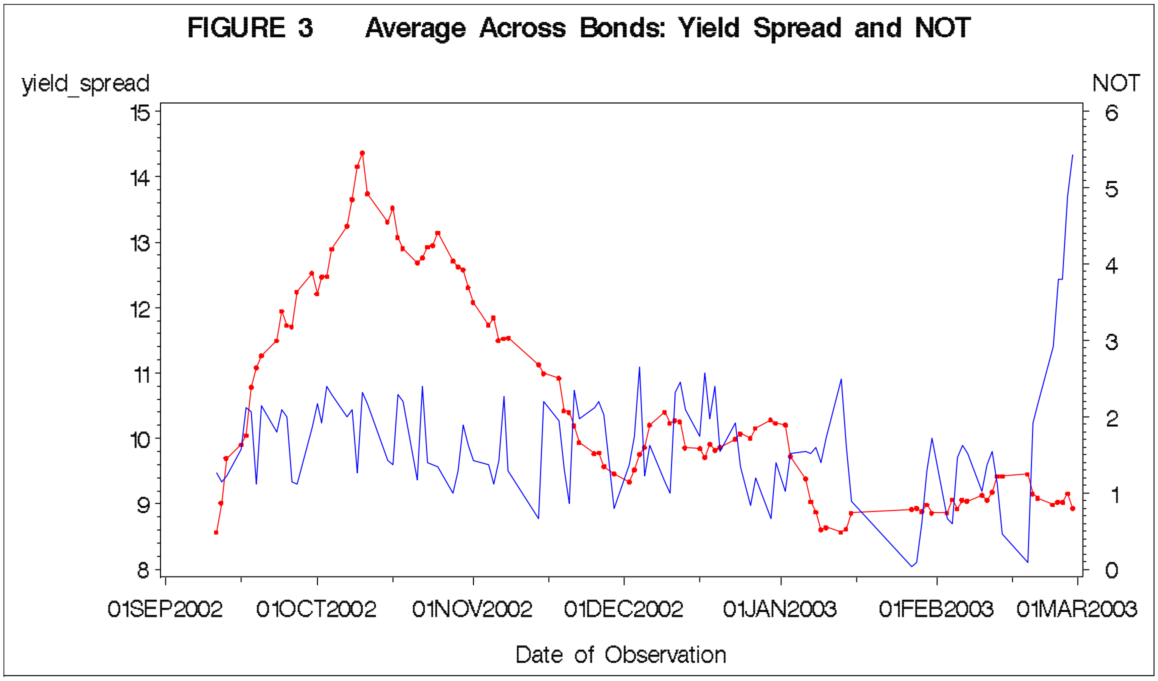
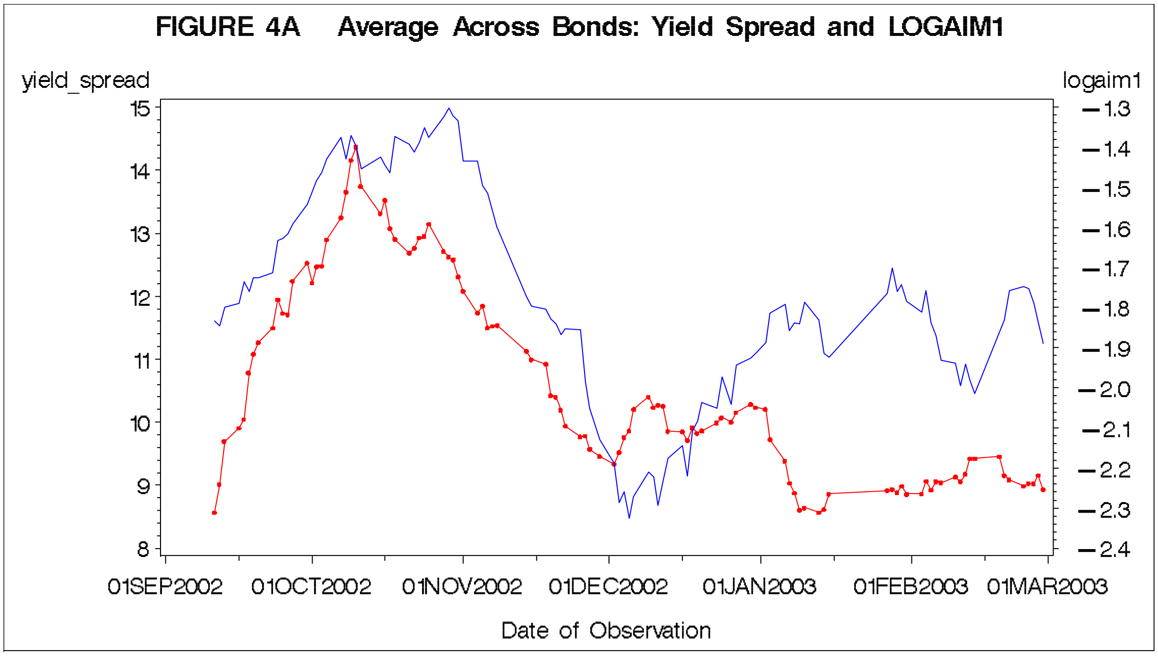


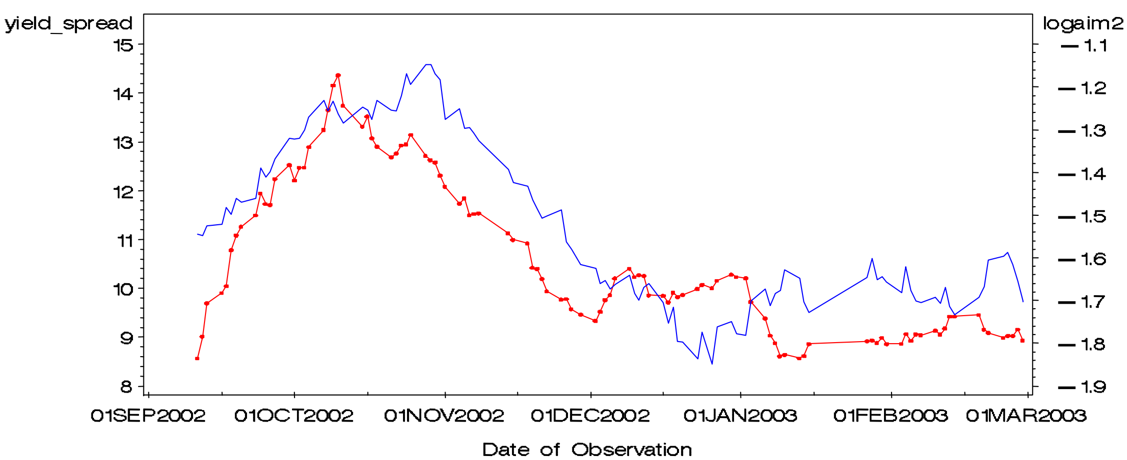
Figure 2.3 Liquidity and Corporate Yield Spreads

This figure plots the liquidity measure (NOT) alongside Corporate Yield Spreads for the 35 TRACE 50 corporate bonds during the period from September 11th to February 28th, 2003, one day before the NASD started its phase II implementation of public corporate bond transaction reporting through the TRACE system. The dotted line represents corporate yield spreads, which are plotted against the left vertical axis, while the solid line denotes the number of trades (NOT), which are plotted against the right vertical axis. The data set consists of 107 daily observations.

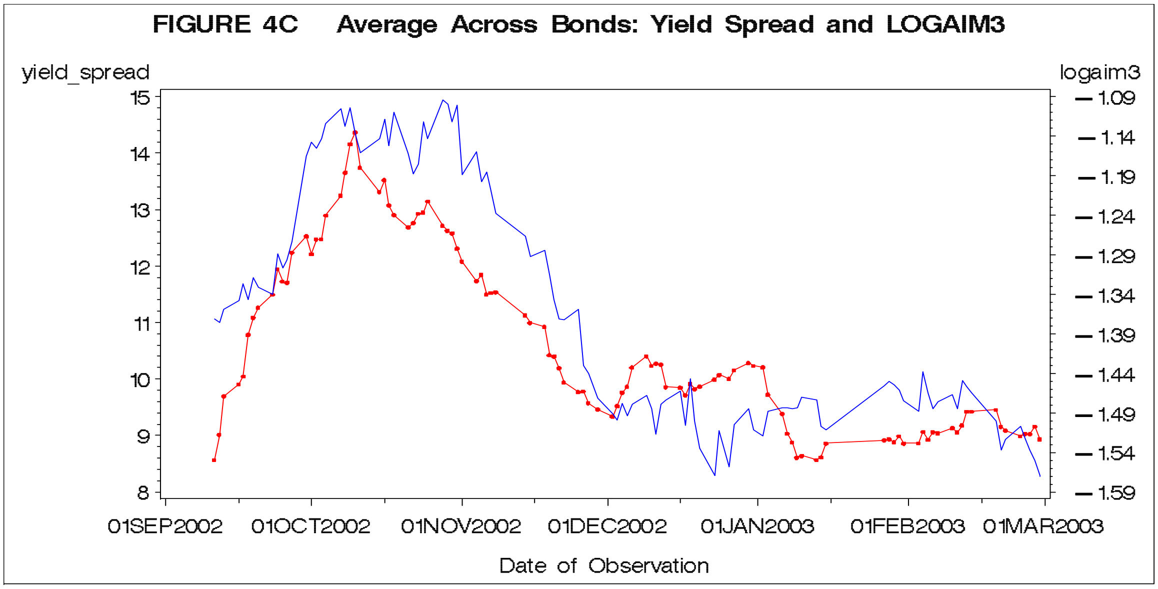


Panel A

B Average Across Bonds: Yield Spread and LOGAIM2



Panel B



Panel C

Figure 2.4 AIM measures and Corporate Yield Spreads

The 3 figures above plot the cross-sectional average of daily time series of corporate yield spreads and the log transformation of the AIM measures for the 35 TRACE 50 corporate bonds during the period from September 11th to February 28th, 2003, one day before the NASD started its phase II implementation of public corporate bond transaction reporting through the TRACE system. The dotted line represents corporate yield spreads, which are plotted against the left vertical axis, while the solid line denotes the AIM measures (logaim1-logaim3), which are plotted against the right vertical axis. AIM measures (logaim1- logaim3) are obtained by performing the transformation (2.13) on AIM1 through AIM3, which correspond to specifications (2.14)-(2.16) respectively. The data set consists of 107 daily observations.

Regression Analysis

Following a brief examination of the correlations between corporate yield spreads and the AIM and liquidity measures, this subsection turns to benchmark regressions, which analyze the impact of private information and liquidity on corporate yield spreads. To explore how the time-variation in private information content and liquidity of corporate bonds affect yield spreads on an individual basis, the following empirical models are estimated based on the panel data of 35 bonds across 107 trading days:

(2.18) $YS_{i,t} = \gamma_0 + \gamma_1 AIM_{i,t} + \varepsilon_{i,t}$,

(2.19) $YS_{i,t} = \gamma_0 + \gamma_2 NOT_{i,t} + \varepsilon_{i,t}$,

and

(2.20) $YS_{i,t} = \gamma_0 + \gamma_1 AIM_{i,t} + \gamma_2 NOT_{i,t} + \varepsilon_{i,t}$,

where $YS_{i,t}$ stands for the yield spread of bond *i* in day *t*, and $\varepsilon_{i,t}$ is the mean-zero error term. All these regressions are pooled, imposing the same coefficients both over time and across different bonds. These models are estimated for three alternative AIM specifications (*LOGAIM1*, *LOGAIM2 and LOGAIM3*), and the estimation results are presented in Table 2.4.

Table 2.4: Benchmark Regressions with Alternative AIM Measures

Panel 1: Private Information Content Measure by LOGAIM1

	REGRESSION 7		REGRESSION 9			
	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	12.938	12.25	13.036	12.30	11.376	11.98
AIM	1.336	20.22	1.336	20.21	1.176	18.23
NOT			-0.059	-1.7		
ILLQ					0.079	3.17
R-Square	0.098		0.099		0.118	

Panel 2: Private Information Content Measured by LOGAIM2

	REGRESSION 7		REGRESSION 9			
	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	13.457	12.72	13.552	12.77	12.731	9.83
AIM	1.898	21.3	1.897	21.29	1.367	15.85
NOT			-0.058	-1.67		
ILLQ					0.103	2.77
R-Square	0.108		0.109		0.123	

Panel 3: Private Information Content Measure by LOGAIM3

	REGRESSION 7		REGRESSION 9			
	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	13.179	12.48	13.257	12.51	11.78	10.75
AIM	1.916	16.98	1.912	16.94	1.19	7.43
NOT			-0.05	-1.41		
ILLQ					0.08	4.11
R-Square	0.072		0.072		0.89	

Panel 4: Liquidity and Yield Spreads

	REGRESSION 8			
	Est.	t-stat	Est.	t-stat
Constant	10.669	10.21	8.765	7.34
NOT	-0.064	-1.73		
ILLQ			0.079	5.11
R-Square	0.001		0.007	

This table reports the results from estimating regression (2.18)-(2.20) based on the panel data of 35 TRACE 50 bonds across 107 trading days. Results from estimating *regression (2.18) and (2.20) for three alternative AIM measures are presented in Panel 1, Panel 2 and Panel 3 respectively. Panel 4 contains results for regression (2.19). For each regression, I report the estimates of coefficients and their associated t-statistics and p-value, together with the resulting R-Square. The dependent variable, YS (yield spread), is calculated as the difference between the corporate bond yield and the yield on a default-free bond with exactly the same maturity and coupon size. Yield on the corresponding default-free bond is estimated by employing a modified version of the extended Nelson-Siegel model [Bliss (1997)] on the observed on-the-run Treasury curve. NOT and ILLQ stand for number of trades and Amihud's illiquidity measure. AIM measures (LOGAIM1- LOGAIM3) are obtained by performing the transformation (2.13) on AIM1 through AIM3, which correspond to specifications (2.14)-(2.16) respectively.*

My primary interest lies in the estimates of λ_1 and λ_2, i.e., the coefficients for AIM and NOT (or ILLQ). My hypothesis concerning the liquidity effect is that since a decrease in the liquidity of a corporate bond (or equivalently an increase in the illiquidity) increases its transaction costs, and hence the required returns on this bond (the yield), a significant negative coefficient for NOT (or a significant positive coefficient for ILLQ) should be expected. As to the influence from information-based trading in corporate bonds, my hypothesis is that a higher degree of information asymmetry in a bond translates to a wider yield spread for that bond; therefore I expect significant positive coefficients for alternative AIM measures.

Table 2.4 presents intriguing results. I find that liquidity (measured by NOT) has an expected negative effect on corporate yield spreads, consistent with previous studies which examine cross-sectional liquidity effects on corporate yield spreads. The estimate of λ_2 in regression (2.19) is -0.064, and has a t-value of -1.73, marginally significant at the 10% level. To better understand the economic significance of the liquidity effect, it is helpful to go back to the summary statistics for NOT reported in Table 2.3. The cross-sectional average of time-series standard deviation of NOT is 1.315, which means that a one-standard-deviation drop in liquidity leads to a widening of the yield spread by more than 8 basis points. Using ILLQ yields a more significant liquidity effects. A coefficient of 0.079 indicates that a one-standard-deviation drop in liquidity causes the yield spread to increase by more than 53 basis points. The finding that corporate yield spreads are subject to changes in the liquidity of corporate bonds indicates a liquidity component in the yield of corporate bonds. The R-Square of this regression, however, is fairly small (0.1% for NOT and 0.7% for ILLQ), suggesting that liquidity alone has limited explanatory power for yield spreads.

Compared to the liquidity of individual bonds, private information content, estimated by alternative AIM measures, imposes much stronger effects on corporate yield spreads. The estimate of λ_1 in regression (2.18) is statistically significant at the 1% level and presents the expected sign, regardless of which specification of the AIM measure is employed. The magnitude of the estimates is quite large. Depending on which specification is used for the AIM measure, this number varies from 1.336 (for LOGAIM1) to 1.916 (for LOGAIM3). Together with the summary statistics for AIM measures in Table III, this suggests that a one-standard-deviation jump in the degree of information asymmetry of a corporate bond causes the bond's yield spread to increase by 73 basis points, if LOGAIM1 is used as a proxy for asymmetric information. For the other AIM measures, LOGAIM2 and LOGAIM3, this number becomes 78 and 65 respectively. The R-square value of regression (2.18) is much larger than that of regression (2.19) where the liquidity measure is used as the repressor. For example, when the first AIM measure (LOGAIM1) is used in regression (2.18), the R-square is 0.098, meaning that information alone explains about 10% of the corporate yield spreads. R-square values for regression (2.19) using LOGAIM2 and LOGAIM3 are 0.108 and 0.072 respectively. Furthermore, the strong information effects persist even when the liquidity measure is added into the model [see the results of regression (2.20)]. The estimate of λ_1 is still statistically significant at the 1% level and remains positive. Several recent studies on information risk as a determinant of stock returns [for example, Easley et al (2002) find that a difference of 10 percentage points in PIN between two stocks leads to a difference of 2.5 percent annual return; Burlacu et al (2005) argue that their AIM measure has a strong impact on stock returns and dominates traditional factors of risk such as β and the Fama and French factors]. In line with this, the results of this paper present striking evidence that information is an important factor in determining the corporate yield spread, and the risk of information-based trading is also priced in the yield of corporate bonds.

Robustness and Sensitivity Analysis

To check the robustness of the benchmark results, I consider in this section several extensions of the original model. First, I exclude from the sample those bonds which have special features that would subject their value to information-based trading. After that, I add to the model several factors from corporate bond pricing literature that have been shown to have some explanatory power for corporate yield spreads.

Embedded Options

High-yield corporate bonds typically have special features, such as embedded options, that would result in their being priced differently. If options are attractive to traders with superior information about the issuer's assets, as extensively supported [see for example, Black (1975), Easley, O'Hara and Srinivas (1998); For an overview of the literature on informed trading in the options markets, see Zhou (2005a)], the high sensitivity of a bond's yield spread to the degree of information asymmetry identified in section 4 might simply be reflective of the relation between the bond's embedded options and the information-based trading. To get rid of this potential bias, all bonds with embedded call or put options or sinking fund provisions, and bonds with floating-rate coupon payments were eliminated. Since all TRACE 50 bonds are nonconvertible, no bonds were excluded for that reason, leaving a panel of 21 bonds across 107 trading days.

Table 2.5 presents strong evidence of the liquidity and information effects on corporate yield spreads. Compared to the benchmark regression results when all 36 TRACE 50 bonds are included (provided in Table IV), the coefficient for liquidity (measured by NOT) in regression (8) continues to be negative, but its significance level increases, both statistically and economically. The t-statistics for λ_2 in regression (8) changes from -1.73 to -2.02, bringing the significance to a level lower than 5%. The estimate for λ_2 (when NOT is used as a measure for liquidity) is now -0.1, indicating that a one-standard-deviation fall in liquidity leads to a jump of the yield spread by more than 13 basis points (it is a 57 basis point if ILLQ is used to measure liquidity). Even though the explanatory power of liquidity remains small, with an R-square of 0.2% for regression (8), it is higher than when bonds with special features were included in the sample.

Table 2.5: Benchmark Regressions with Alternative AIM Measures on bonds without special features

Panel 1: Private Information Content Measure by LOGAIM1

	REGRESSION 7		REGRESSION 9			
	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	12.975	9.13	13.134	9.21	9.881	10.54
AIM	1.596	17.74	1.595	17.74	1.497	15.67
NOT			-0.096	-2.08		
ILLQ					0.087	1.91
R-Square	0.123		0.125		0.139	

Panel 2: Private Information Content Measured by LOGAIM2

	REGRESSION 7		REGRESSION 9			
	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	13.338	9.39	13.461	9.44	14.234	10.39
AIM	2.1	17.83	2.095	17.78	1.589	16.05
NOT			-0.079	-1.7		
ILLQ					0.074	3.13
R-Square	0.124		0.125		0.147	

Panel 3: Private Information Content Measure by LOGAIM3

	REGRESSION 7		REGRESSION 9			
	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	13.24	9.33	13.328	9.35	10.239	8.53
AIM	2.271	15.09	2.26	15.19	1.963	11.75
NOT			-0.062	-1.31		
ILLQ					0.077	3.21
R-Square	0.092		0.093		0.121	

Panel 4: Liquidity and Yield Spreads

	REGRESSION 8			
	Est.	t-stat	Est.	t-stat
Constant	10.456	7.48	9.142	8.37
NOT	-0.1	-2.02		
ILLQ			0.085	4.17
R-Square	0.002		0.083	

This table reports the results from estimating regression (2.18)-(2.20) based on the panel data of 21 TRACE 50 bonds across 107 trading days. These 21 bonds have constant semiannual coupon payments, and no embedded options (convertible, callable or sinking fund provisions). Results from estimating regression (2.18) and (2.20) for three alternative AIM measures are presented in Panel 1, Panel 2 and Panel 3 respectively. Panel 4 contains results for regression (2.19). For each regression, I report the estimates of coefficients and their associated t-statistics and p-value, together with the resulting R-Square. The dependent variable, YS (yield spread), is calculated as the difference between the corporate bond yield and the yield on a default-free bond with exactly the same maturity and coupon size. Yield on the corresponding default-free bond is estimated by employing a modified version of the extended Nelson-Siegel model [Bliss (1997)] on the observed on-the-run Treasury curve. NOT stands for number of trades, which is used as a measure for liquidity in this paper. AIM measures (LOGAIM1- LOGAIM3) are obtained by performing the transformation (2.13) on AIM1 through AIM3, which correspond to specifications (2.14)-(2.16) respectively.

What is more surprising, however, is that information effects remain strong, and even become slightly stronger when bonds with embedded options are eliminated. Re-estimation of regression (2.19) shows that the coefficients for the AIM measures increase and are still significant at the 1% level, no matter which specification is used. The estimates of the coefficients for LOGAIM1, LOGAIM2 and LOGAIM3 in regression (2.19) move from 1.336, 1.898 and 1.916 to 1.596, 2.1 and 2.271 respectively. This implies that if the degree of information asymmetry of a corporate bond (measured by LOGAIM1) goes up by one-standard-deviation, the yield spread of this bond will rise 87 basis points[43]. Furthermore, the explanatory power of the information factor increases. The R-square becomes 12.3%, 12.4% and 9.2% for the regression (2.18) with AIM specified by LOGAIM1, LOGAIM2 and LOGAIM3 correspondingly. Finally, even after accounting for liquidity differences, the private information content of a corporate bond continues to be a significant factor influencing corporate bond yield spreads (see Table 2.5).

Traditional Factors Affecting Corporate Yield Spreads

Within traditional corporate bond pricing literature, several factors have already been identified as determinants of corporate yield spreads. To make the argument that information and liquidity provide additional explanatory power for yield spreads, it is important to test whether these microstructure factors are simply proxies for traditional yield spread determinants. Therefore, the regression model in equation (2.20) is expanded to include the following independent variables:

Credit Ratings. Previous studies have shown that credit ratings[44] of corporate bonds affect their yield spreads [see for example, Campbell and Taksler (2003) and Cremers, Driessen, Maenhout and Weinbaum (2004)]. Since this study focuses on a relatively small number of high-yield corporate bonds, I aggregate the different ratings by Standard and Poor's (S&P) into 3 groups: Rating Group 1 includes bonds rated no lower than BB- by S&P. Rating Group 2 consists of the B level bonds, and all the

[43] It is 86 and 77 basis points for LOGAIM2 and LOGAIM3, respectively.

[44] The credit rating of a corporate bond is not a perfect measure for credit risk, as several studies have shown that there is a lag between changes in credit risks and credit rating migrations [see for example, Cremers, Driessen, Maenhout and Weinbaum (2004)]. Since this paper is not focusing on modeling the dynamics of credit risks, I follow Campbell and Taksler (2003) by using credit rating as a control for bond credit risks.

other bonds which are rated no higher than CCC+ are left in Rating Group 3.

Level and slope of the Term Structure of Treasury Rate. Longstaff and Schwartz (1995) argue in their model that an increase in risk-free interest rates implies an upward drift in the risk-neutral process for the value of the firm, (which means that firm value drifts away for the financial distress threshold at a faster rate as the interest rate rises), and hence a reduction in the risk-neutral probability of default and corporate yield spread. The negative relation between the risk-free interest rate and corporate yield spreads predicted by the model was empirically supported in their paper. Following Collin-Dufresne, Goldstein and Martin (2001) and Cremers, Driessen, Maenhout and Weinbaum (2004), among others, I use the 10-year Treasury rate to describe the level of the term structure. I also include the squared level of the 10-year Treasury rate, as in Collin-Dufresne, Goldstein and Martin (2001), to capture potential nonlinear effects due to convexity. Even though all of these studies also calculate the difference between the 10- and 2- year Treasury rates to describe the slope of the term structure, and use it to measure the expectation of future short rates and overall economic health, empirical evidence of its effect on yield spreads is rather limited [see for example Collin-Dufresne, Goldstein and Martin (2001) and Campbell and Taksler (2003)]. Therefore, I only use the daily series of 10-year Treasury rates from the CRSP Daily Fixed Term Indices File.

Implied Volatilities of Individual Options. In a recent paper, Cremers, Driessen, Maenhout and Weinbaum (2004) show that option implied volatilities contain important information for corporate yield spreads. To test whether my AIM measures are simply picking up volatility risk, implied volatilities of the options for those firms that have their bonds included in my sample were added. If the AIM measures are correlated with implied volatilities of individual options, the coefficients on AIM measures should shrink to zero when a direct proxy for volatility risk is added to the model. Following Cremers, Driessen, Maenhout and Weinbaum (2004), for each individual bond, I retrieve from OptionMetrics, LLC the daily data on the implied volatility of at-the-money put options on the issuer's common stock.

Liquidity of Issuer's Options. If firm-specific credit risk in a corporate bond can be somewhat hedged by trading in individual options of its issuer, the liquidity of the market for these options may have an influence on the bond's yield spread. When the liquidity for the issuer's options dries up, hedging the corporate bond becomes difficult and costly. A higher yield spread thus will be required to compensate for that cost. This hypothesis is empirically supported by Cremers, Driessen, Maenhout and Weinbaum (2004). They find some evidence that individual options do have liquidity-spillover effects on the corporate bonds. Furthermore, if the liquidity of a corporate bond is correlated with the liquidity of the issuer's traded options, the significance of the liquidity measure for corporate bonds in the benchmark regression might simply reflect the liquidity-spillover effects mentioned above.

Lagged Stock Returns. Leading effects of stocks on corporate bonds have been documented in several studies [see for example, Kwan (1996), Collin-Dufresne, Goldstein and Martin (2001), Campbell and Taksler (2003) and Zhou (2005a)]. Therefore, I also include the one-day lagged S&P 500 return as a regressor.

By including all these additional variables, the benchmark regression is expanded as follows:

(2.21)

$$YS_{i,t} = \gamma_0 + \gamma_1 AIM_{i,t} + \gamma_2 NOT_{i,t} + \gamma_3 RGTWO_i + \gamma_4 RGTHREE_i + \gamma_5 TENYR_t$$
$$+ \gamma_6 OPTVOL_{i,t} + \gamma_7 OPTLIQ_{i,t} + \gamma_8 SP_{t-1} + \varepsilon_{i,t},$$

where RGTWO and RGTHREE denote the dummy variables for Rating Group two and Rating Group three; TENYR stands for the ten-year interest rate; OPTVOL and OPTLIQ represent the implied-volatility and liquidity of the at-the-money put option by the issuer, and SP symbolizes the S&P 500 return. Results from estimating this model are presented in Table 2.6.

Table 2.6: Regressions with Traditional Corporate Yield Spreads Determinants

Panel 1 Private Information Content Measure by LOGAIM1

	Est.	t-stat	Est.	t-stat
Constant	12.808	3.6	11.793	4.21
AIM	1.311	14.32	1.19	11.28
NOT	-0.1	-2.26		
ILLQ			0.078	3.77
RGTWO	8.435	3.19	7.142	2.98
RGTHREE	10.558	2.41	11.649	1.98
TENYR	-1.756	-2.28	-1.926	-3.19
OPTVOL	2.997	10.33	2.756	9.43
OPTLIQ	-0.928	-2.64	-0.879	-2.76
SP	9.417	1.21	8.39	1.13
R-Square	15.40%		16.87%	

Panel 2 Private Information Content Measure by LOGAIM2

	Est.	t-stat	Est.	t-stat
Constant	14.271	4.12	15.219	3.18
AIM	1.801	15.48	1.593	11.85
NOT	-0.089	-2.03		
ILLQ			0.067	3.16
RGTWO	8.526	3.19	7.924	3.19
RGTHREE	10.804	2.44	11.017	3.05
TENYR	-2.024	-2.74	-2.731	-3.16
OPTVOL	2.879	9.95	2.817	8.43
OPTLIQ	-0.916	-2.62	-0.105	-2.73
SP	10.077	1.35	8.93	1.15
R-Square	16.70%		17.72%	

Table 2.6 (Continued)

Panel 3 Private Information Content Measure by LOGAIM3

	Est.	t-stat	Est.	t-stat
Constant	13.884	3.86	11.759	4.01
AIM	1.918	12.59	1.497	10.73
NOT	-0.072	-1.61		
ILLQ			0.083	2.97
RGTWO	8.357	3.16	8.156	2.98
RGTHREE	10.765	2.45	11.01	2.78
TENYR	-1.903	-2.43	-1.876	-2.13
OPTVOL	2.845	9.65	2.759	8.75
OPTLIQ	-1.336	-3.76	-1.537	-2.78
SP	11.053	1.4	9.136	0.87
R-Square	13.70%		15.01%	

This table reports the results from estimating regression (2.21) based on the panel data of 21 TRACE 50 bonds across 107 trading days. These 21 bonds have constant semiannual coupon payments, and no embedded options (convertible, callable or sinking fund provisions). Results for three alternative AIM measures are presented in Panel 1, Panel 2 and Panel 3 respectively. For descriptions about the yield spread (YS), AIM measures (AIM) and liquidity measures (NOT and ILLQ), see Table VIII. RGTWO and RGTHREE denotes the dummy variables for credit group two and credit group three respectively. TENYR stands for the ten-year interest rate. OPTVOL and OPTLIQ represent the implied-volatility and liquidity for the at-the-money put option for the issuer, and SP symbolizes the S&P return.

It is intriguing to observe that liquidity and AIM measures for individual corporate bonds continue to play important roles in determining corporate yield spreads. Coefficients for both liquidity and information asymmetry remain statistically significant and present the expected signs. Furthermore, these factors prove to be economically meaningful in explaining yield spreads. The coefficient of -0.1 for NOT (0.078 for ILLQ) implies that a one-standard-deviation shock to the liquidity of a corporate bond moves its yield spread by more than 13 basis points (52 basis points), when the first specification of the AIM measure is used in the regression. This impact (from NOT) changes slightly when different AIM measures are employed [about 11 basis points and 9 basis points for the second and the third AIM measures respectively]. Compared to the liquidity effect, information-based trading has a larger influence on the corporate yield spread. For the AIM measure specified by equation (2.14), the coefficient of 1.311 indicates that a one-standard deviation increase in the degree of information asymmetry of a corporate bond is associated with a widening of the bond's yield spread by 71 basis points. The change in the yield spread becomes 74 and 65 basis points when specification 2 and specification 3 are chosen for the AIM measure. The extreme robustness of these results supports my hypothesis that information-based trading risks, as well as the transaction costs of liquidity, assume important roles in explaining corporate yield spreads. Valuation of risky corporate debt needs to be recast to incorporate these market microstructure factors, which have long been ignored in the literature.

To finish up the robustness check of my results, it is necessary to examine the traditional corporate bond pricing factors. Consistent with earlier work, coefficients for all of these extra variables are statistically significant and carry the expected signs, except for the S&P 500 market return. This result, however, is not that surprising, as Collin-Dufresne, Goldstein and Martin (2001) also find that this coefficient is not significant and presents the wrong sign for higher leverage (lower rated) bonds, which are the focus of this study. Turning to other factors, the credit rating of a corporate bond continues to bring economically meaningful differences in yield spreads. Lower rated bonds tend to have higher yield spreads. The level of risk-free interest rates, measured by the 10-year treasury rate, has a significant negative effect on yield spreads, in line with the argument made by Longstaff and Schwartz (1995). Finally, the options market contains valuable information in explaining corporate yield spreads. Implied volatilities of at-the-money put options on the issuer's common stock are shown to be useful proxies for volatility risk, which directly affect the yield spread of the issuer's debt securities, reinforcing the findings by Cremers, Driessen, Maenhout and Weinbaum (2004). The liquidity of a firm's traded options has significant negative effects on the yield spread of its bond, again confirming the liquidity spill-over effects documented by Cremers, Driessen, Maenhout and Weinbaum (2004).

Conclusion

Taking advantage of a recently available corporate bond transaction dataset from the National Association of Securities Dealers (NASD), as well as a new measure for the degree of information asymmetry derived from a multi-security rational expectations model, I have demonstrated in this paper that market microstructure factors, including information and liquidity, possess additional explanatory power in explaining the actual yield spreads of risky corporate bonds. A one-standard-deviation drop in liquidity (measured by NOT) leads to a widening of the yield spread by more than 13 basis points (by 52 basis points when ILLQ is used), and a one-standard-deviation jump in the degree of information asymmetry of a corporate bond causes the bond's yield spread to increase by 71 basis points, after controlling for the effects from traditional corporate bond pricing models. Liquidity (measured by trade frequency) and information (measured by AIM) alone explain about 10% of the corporate yield spreads. This paper extends the recent literature on the implications of market microstructure for asset pricing [initiated by Easley and O'Hara (2004)] to the corporate bond market, and suggests that yields of corporate debt might embed both an information premium and a liquidity premium that are ignored by existing corporate bond pricing models. Therefore, valuation of corporate debt needs to be recast in broader terms to integrate the transaction costs of liquidity and risks from information asymmetry during the process of price discovery.

Furthermore, this paper also suggests that the information structure surrounding a firm's debt has important effects on its financing and risk management decisions. If there is enormous information-based trading in a firm's risky bonds, investors will require higher yields to hold these bonds, and hence the firm will be less willing to issue bonds in equilibrium. This study, consistent with Easley and O'Hara (2004), implies that a firm can affect its cost of debt by choosing analyst coverage, disclosure policy, market microstructure, accounting treatments and any other factors that will influence the information structure surrounding its debt securities. It provides a new perspective to understand the complete market assumption in the Modigliani and Miller Theorem.

Finally, recent research has started to look beyond the traditional bond pricing framework for better explanations of the credit spread puzzle. Odders-White and Ready (2004) show that microstructure measures of adverse selection in the equity securities are larger when credit ratings of the issuer's bonds are poor. Yu (2005) finds that firms with higher accounting transparency tend to have lower credit spreads. The main contribution of this paper is that I establish a significant link between corporate yield spreads and two main market microstructure factors: information and liquidity. Whether these factors completely solve the yield spread puzzle in the finance literature is not addressed in this paper, but constitutes a very interesting and important topic for further research. This topic in turn, requires an estimation of the information risk premium and liquidity premium, as well as a theoretical corporate bond pricing model which explicitly incorporates the information risk and liquidity costs. Research in this direction is currently under way.

APPENDIX

Estimation Default-Free Zero-Coupon Interest Rates by Using the Extend Nelson-Siegel Model

The extended Nelson-Siegel Model fits an exponential approximation of the discount rate function directly to observed bond prices. In this model, the bond pricing function is simply

$$\hat{p}_i = \sum_{m=1}^{M_i} c_{i,m} e^{-r(m)m},$$

where c and m refer to the cash flow and its related time respectively. The discount rate function, r(m), takes the following functional form:

$$r(m) = \beta_0 + \beta_1 \left[\frac{1 - e^{-m/\tau_1}}{m/\tau_1} \right] + \beta_2 \left[\frac{1 - e^{-m/\tau_2}}{m/\tau_2} - e^{-m/\tau_2} \right].$$

A set of parameters, $\Phi = [\beta_0, \beta_1, \beta_2, \tau_1, \tau_2]$, is estimated using the following nonlinear constrained optimization estimation procedure:

$$\min_{\beta_0, \beta_1, \beta_2, \tau_1, \tau_2} \sum_{i=1}^{N_t} (w_i \varepsilon_i)^2,$$

subject to

$$r(m_{\min}) \geq 0,$$

$$r(m_{\max}) \geq 0,$$

and

$$\exp[-r(m_k)m_k] \geq \exp[-r(m_{k+1})m_{k+1}], \quad \forall m_{\min} \leq m_k < m_{\max},$$

where

$$w_i = \frac{1/d_i}{\sum_{j=1}^{N_t} 1/d_j},$$

and

$$\varepsilon_i = p_i - \hat{p}_i.$$

In this model, d denotes the Macaulay duration and ε_i is the pricing error. With the estimates $\hat{\Phi} = [\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\tau}_1, \hat{\tau}_2]$, the discount rate r(m), the default-free zero-coupon interest rate, and thereafter the price and the yield of the corresponding default-free bonds can be readily calculated.

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