Information, Liquidity and Corporate Yield Spreads

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ABSTRACT

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. This paper demonstrates that in addition to liquidity, information asymmetry plays an important role in determining yield spreads of risky corporate bonds. In line with a strand of recent literature on the implications of market microstructure for asset pricing, this paper suggests corporate bond yields might embed an information risk premium that is ignored by existing bond pricing models.

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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[1] 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 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,

[1] 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).

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[2], 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 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

[2] 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).

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."[3]

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.[4] Since illiquidity prevents investors from 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)[5] by the National Association of Securities Dealers (NASD). Because of this, empirical research in this area has relied on indirect liquidity measures,[6] including the total amount of a bond issue [Alexander,

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

[4] 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).

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

[6] 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.

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)].[7] Houweling, Mentink and Vorst (2003) propose two additional measures: the occurrence of 'price runs'[8] or missing values, and the dispersion of yields quoted from different sources[9]. 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-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[10].

While these different liquidity measures provide more insight into the determinants of yield spread changes, their added explanatory power is rather limited.

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[7] 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).

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

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

[10] 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.

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. 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)[11]. 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 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.[12] 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."[13]

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

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

[12] The Wall Street Journal, 10/31/2001.

[13] 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.

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 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 I 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 II describes the data used for this study with special emphasis on corporate bond transaction data from the NASD's TRACE system. Section III contains summary descriptions of the results from estimating the private information content of individual corporate bonds. In section IV, 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 V. I conclude my arguments in section VI.

I. 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.

A. 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:

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

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*:

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

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

$$P = \begin{bmatrix} p_1 & p_2 & p_3 & \dots & p_N \end{bmatrix}',$$

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

$$\Theta = \begin{bmatrix} \mu_1 & \mu_2 & \dots & \mu_N & \theta_1 & \theta_2 & \dots & \theta_K \end{bmatrix}',$$

$$\mathrm{E} = \begin{bmatrix} \varepsilon_1 & \varepsilon_2 & \varepsilon_3 & \dots & \varepsilon_N \end{bmatrix}',$$

$$\text{and } Z = \begin{bmatrix} z_1 & z_2 & z_3 & \dots & z_N \end{bmatrix}'.$$

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

$$P^1 = B\Theta + E,$$

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*:

$$P^0 = A_0 + A_1\Theta - A_2 Z$$

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 as:

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

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.

B. 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:

$$\Delta P_t^i = \alpha^i + \sum_{j=1}^{N} \beta^{i,j} P_{t-1}^j + \varepsilon_t^i \ , \qquad \textbf{(2)}$$

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

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

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*:

$$AIM^i = \ln\left(\frac{R_i^2}{1 - R_i^2}\right). \qquad \textbf{(3)}$$

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.[14]

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:

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

$$\Delta P_t^i = \alpha^i + \beta^{i,b} P_{t-1}^i + \beta^{i,s} S_{t-1}^i + \varepsilon_t^i , \tag{4}$$

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:

$$\Delta P_t^i = \alpha^i + \beta^{i,b} P_{t-1}^i + \beta^{i,s} S_{t-1}^i + \beta^{i,m} M_{t-1}^i + \varepsilon_t^i , \tag{5}$$

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:

$$\Delta P_t^i = \alpha^i + \beta^{i,b} P_{t-1}^i + \beta^{i,df} DF_{t-1}^i + \beta^{i,m} M_{t-1}^i + \beta^{i,s} S_{t-1}^i + \varepsilon_t^i , \tag{6}$$

where *DF* stands for default-free bond.

II. 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.[15] Unlike stocks, the majority of corporate bond transactions take place on the OTC market[16] and no price related information had been available to the public until NASD introduced the Fixed Income Pricing System (FIPS)[17] in 1994, which was later incorporated into a broader system known as TRACE[18] on July 1st,

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15 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.

16 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.

17 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).

18 Zhou (2005a) provides a brief review of recent developments in the corporate bond market, as well as a detailed description of the TRACE system.

2002. Under TRACE rules,[19] all NASD members are obligated to submit transaction reports for any secondary market transaction in TRACE-eligible securities[20] between 8:00PM and 6:30PM (EST) within one hour and fifteen minutes of the time of execution.[21] 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

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19 Also known as the NASD Rule 6200 series.

20 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 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.

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

transaction reports) for every trade in the TRACE 50 high-yield bonds during the period from July 1st, 2002 to September 30th, 2004[22]. 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, 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

[22] 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.

the trading days. By excluding these firms from my sample, I am left with a panel of 36 bonds across 259 trading days.

Table I 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.

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.

III. 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):

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

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 (4)-(6) 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 II.

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 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.[23] Empirical microstructure work, however,

[23] 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).

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 II 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 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.

IV. 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[24]. 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 1 and Figure 2 depict how the main variables change over time, and summary statistics for these variables are reported in Table III.

First, as shown by Figure 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 III, 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

[24] 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.

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 III 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). 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.

A. 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 3 and Panel 2 of Table III. 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 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.

B. 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:

$$YS_{i,t} = \gamma_0 + \gamma_1 AIM_{i,t} + \varepsilon_{i,t}, \qquad \textbf{(7)}$$

$$YS_{i,t} = \gamma_0 + \gamma_2 NOT_{i,t} + \varepsilon_{i,t}, \qquad \textbf{(8)}$$

and

$$YS_{i,t} = \gamma_0 + \gamma_1 AIM_{i,t} + \gamma_2 NOT_{i,t} + \varepsilon_{i,t}, \qquad \textbf{(9)}$$

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 IV.

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 IV 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 (8) 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 III. 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 (7) 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 (7) is much larger than that of regression (8) where the liquidity measure is used as the repressor. For example, when the first AIM measure (LOGAIM1) is used in regression (7), the R-square is 0.098, meaning that information alone explains about 10% of the corporate yield spreads. R-square values for regression (8) 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 (9)]. 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.

V. 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.

A. 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 V 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.

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 (8) 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 (8) 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[25]. Furthermore, the explanatory power of the information factor increases. The R-square becomes 12.3%, 12.4% and 9.2% for the regression (7) 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 V).

B. 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 (9) is expanded to include the following independent variables:

Credit Ratings. Previous studies have shown that credit ratings[26] 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

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

[26] 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.

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 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:

$$\begin{aligned} YS_{i,t} &= \gamma_0 + \gamma_1 AIM_{i,t} + \gamma_2 NOT_{i,t} + \gamma_3 RGTWO_i + \gamma_4 RGTHREE_i + \gamma_5 TENYR_t \\ &+ \gamma_6 OPTVOL_{i,t} + \gamma_7 OPTLIQ_{i,t} + \gamma_8 SP_{t-1} + \varepsilon_{i,t}, \end{aligned} \quad \textbf{(10)}$$

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 VI.

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 (4), 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).

VI. 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.

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Table I

Characteristics of 36 TRACE 50 Bonds and Their Issuing Firms

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).

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

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

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

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 (4)-(6) respectively. LOGAIM1, LOGAIM2 and LOGAIM3 are obtained by performing the transformation (3) 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.

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

Table III

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

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 (3) on AIM1 through AIM3, which correspond to specifications (4)-(6) 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.

Panel 1: Mean and Time-Series Standard Deviations

Variable	Period I		Period II	
	Mean	TS Std. Dev.	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

Table IV
Benchmark Regressions with Alternative AIM Measures

This table reports the results from estimating regression (7)-(9) based on the panel data of 35 TRACE 50 bonds across 107 trading days. Results from estimating regression (7) and (9) for three alternative AIM measures are presented in Panel 1, Panel 2 and Panel 3 respectively. Panel 4 contains results for regression (8). 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 (3) on AIM1 through AIM3, which correspond to specifications (4)-(6) respectively.

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	

Table V

Benchmark Regressions with Alternative AIM Measures on bonds without special features

This table reports the results from estimating regression (7)-(9) 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 (7) and (9) for three alternative AIM measures are presented in Panel 1, Panel 2 and Panel 3 respectively. Panel 4 contains results for regression (8). 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 (3) on AIM1 through AIM3, which correspond to specifications (4)-(6) respectively.

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	

Table VI

Regressions with Traditional Corporate Yield Spreads Determinants

This table reports the results from estimating regression (10) 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.

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%	

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%	

Figure 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.

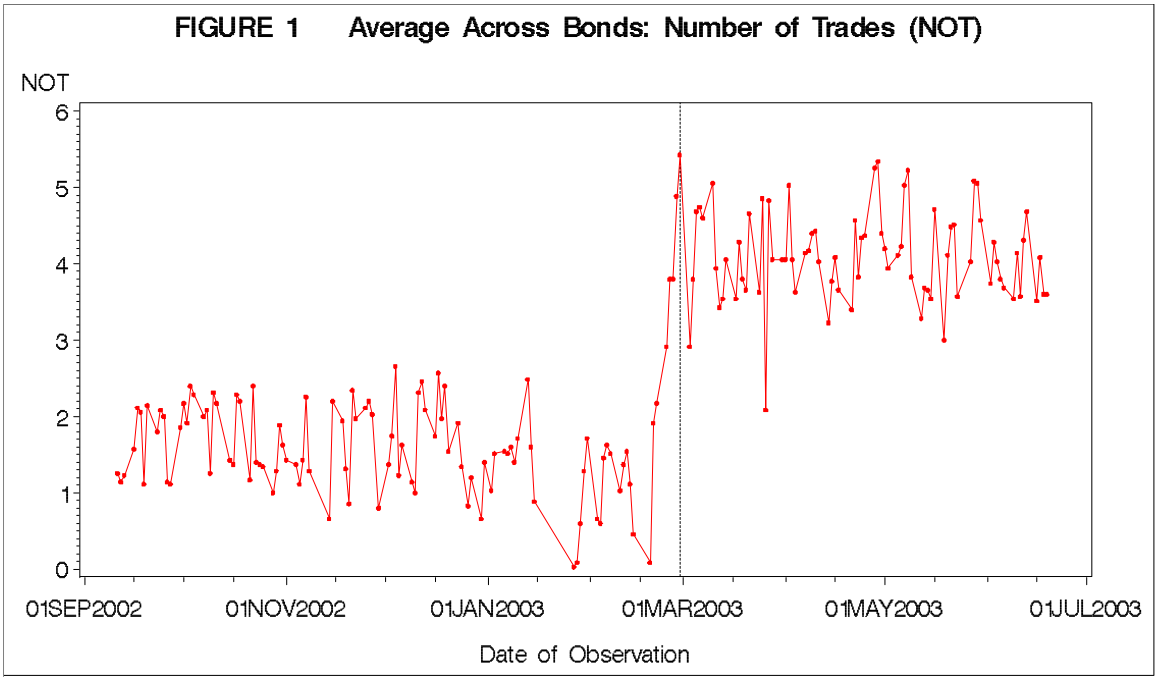


Figure 2
Time-Varying Corporate Yield Spreads

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.

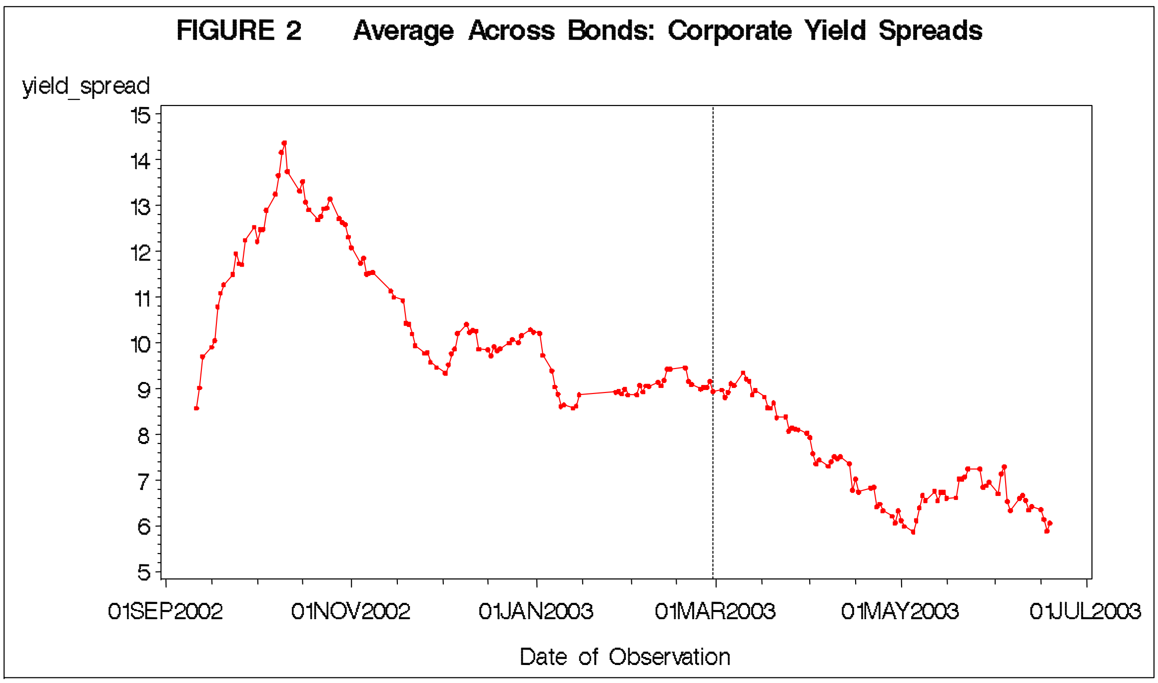


Figure 3
Liquidity and Corporate Yield Spreads

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.

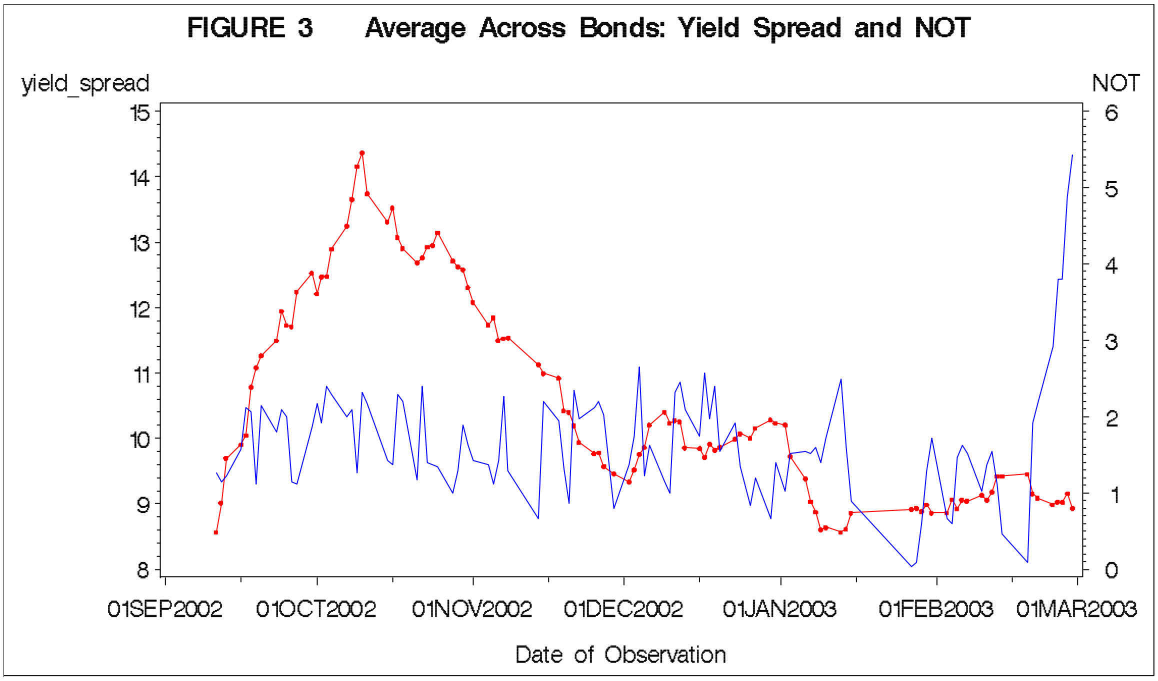


Figure 4

AIM measures and Corporate Yield Spreads

The following 3 figures 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 (3) on AIM1 through AIM3, which correspond to specifications (4)-(6) respectively. The data set consists of 107 daily observations.

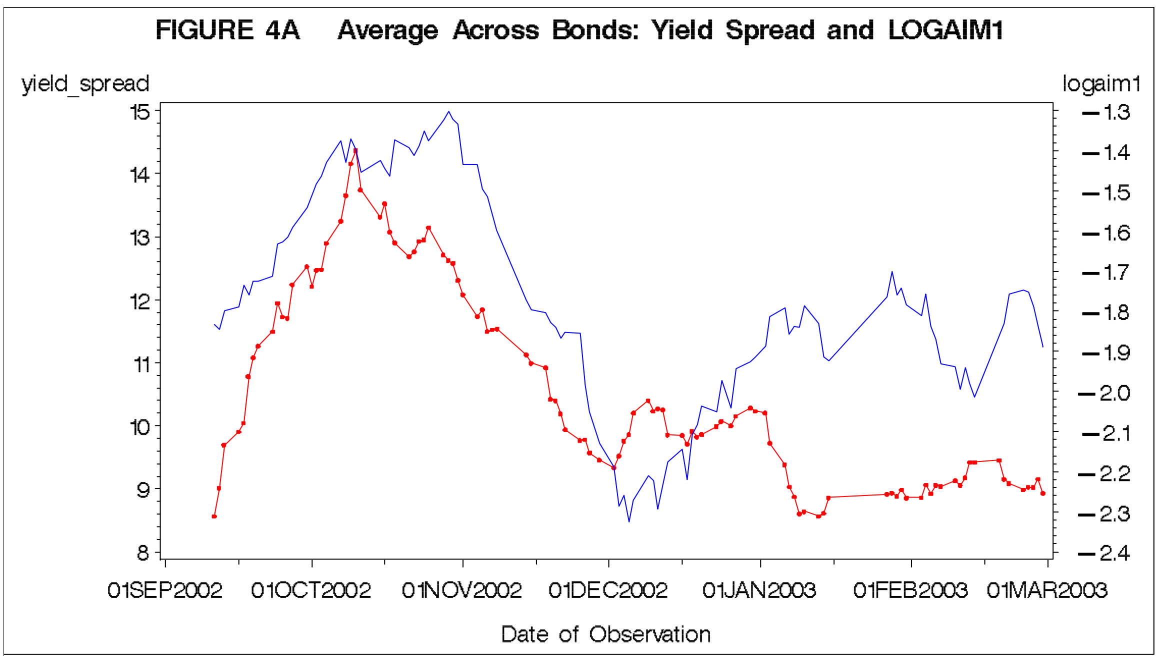


FIGURE 4B Average Across Bonds: Yield Spread and LOGAIM2

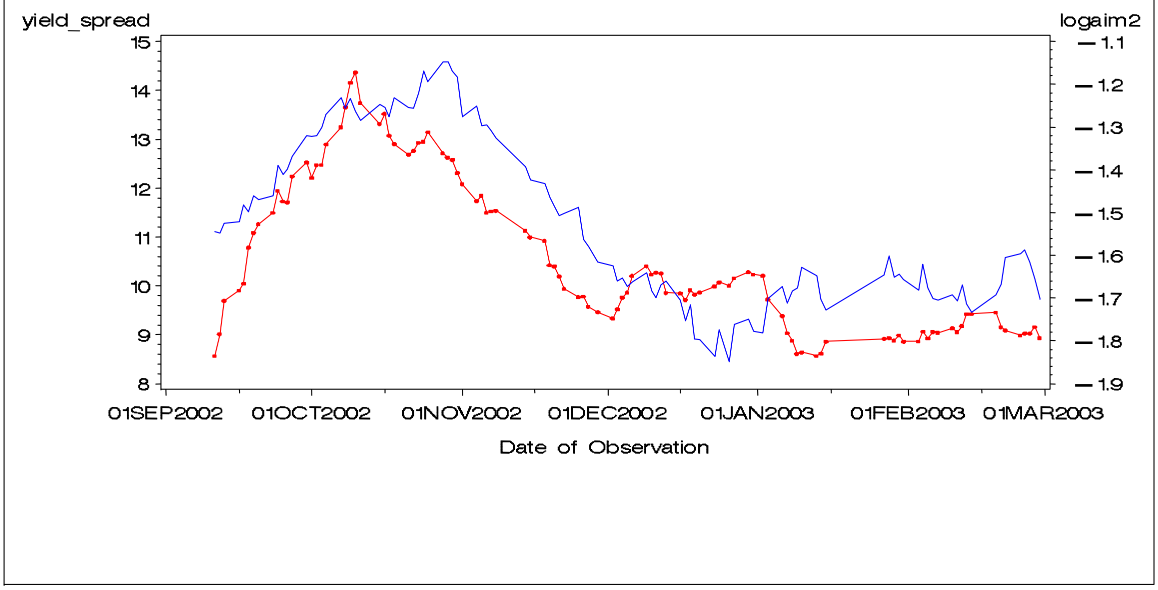
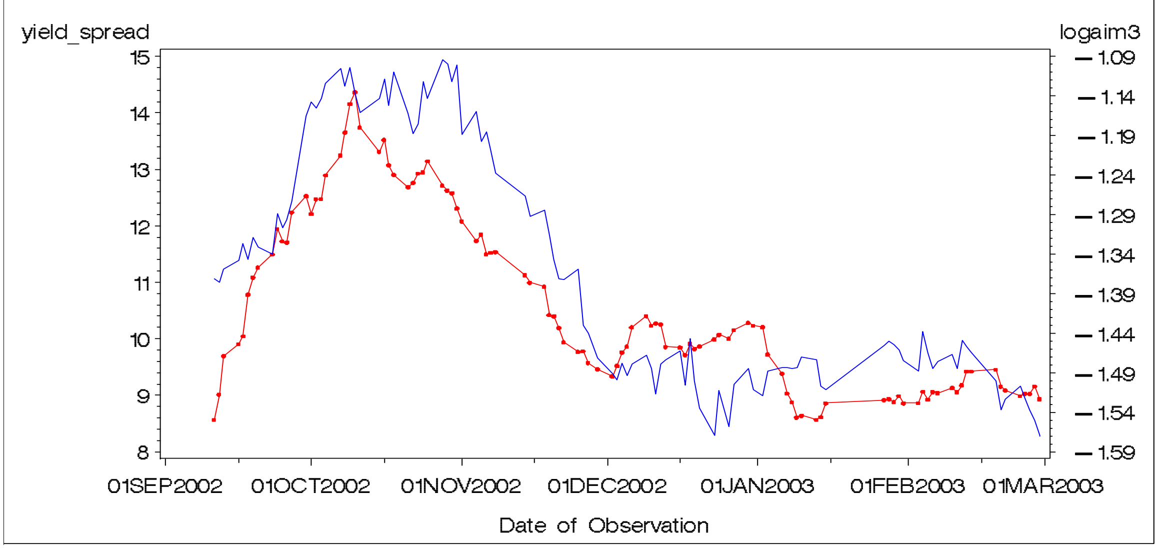


FIGURE 4C Average Across Bonds: Yield Spread and LOGAIM3



Appendix A

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.