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Informed Bond Trading, Corporate Yield Spreads, and Corporate Default Prediction

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Taking advantage of recently augmented corporate bond transaction data, we examine the pricing implications of informed trading in corporate bonds and its ability to predict corporate defaults. We find that microstructure measures of information asymmetry seem to capture adverse selection in corporate bond trading reasonably well. We demonstrate that information asymmetry in bond trading has explanatory power for corporate bond yield spreads, and this result holds after controlling for the transaction costs of liquidity, credit risk, and other traditional bond pricing factors. Furthermore, information asymmetry can help forecast corporate defaults after conditioning on other default prediction variables. Such forecasting ability of informed bond trading is especially useful for private firms because the bond market constitutes the only venue for informed traders to exploit their information advantages.

Keywords: corporate bond yield spreads; information asymmetry; information risk premium; credit risk; corporate default prediction
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1. Introduction

One salient feature of the U.S. corporate bond market is the predominance of institutional trading.[1] Recent work suggests that trading by sophisticated institutions tends to be information based.[2] According to market microstructure theory, the presence of such informed trading can affect bond prices. Because uninformed traders face the risks of losing to informed traders, given a bond's contractual cash flow, lower prices or, equivalently, higher yields are required to hold bonds with more informed trading. Based on this rationale, we examine the degree of information asymmetry in corporate bond trading and its effect on corporate yield spreads. In addition, because bonds are more information sensitive when the issuer is closer to default, we test whether the rise in informed bond trading may help predict corporate defaults.

The possibility of informed trading in the corporate bond market may stem from its institutional nature. First, institutional investors differ significantly in their sophistication levels, and thus some institutions are better able to interpret the value relevance of public information than others (see, e.g., Kandel and Pearson 1995). Second, some institutions may gain information advantages from their privileged access to information. For example, institutional investors who trade corporate bonds, such as hedge funds and mutual funds, often participate in syndicated loans for the same issuer. Because large creditors are entitled to send representatives to regular meetings with the borrowing company's management, they have access to confidential information, such as updated growth projections, covenant negotiations, and merger and acquisition or divestiture plans.[3] Moreover, a single

[1] Institutional investors account for the majority of the ownership and most of the trading volume of corporate bonds. According to the flow of funds accounts of the United States, outstanding corporate bonds issued by U.S. firms totaled about $7 trillion at the end of 2009, the bulk of which were owned by institutional investors. Edwards et al. (2007) report that institutional sized trades (those greater than $100,000 in par value), account for most of the dollar volume of corporate bonds.

[2] For example, Ke and Petroni (2004), Bushee and Goodman (2007), Barber et al. (2009), and Ivashina and Sun (2010) find evidence of informed trading by institutional investors in the equity markets.

[3] Ivashina and Sun (2010) provide some evidence that institutional investors trade stocks based on private information acquired from the loan market. There has also been anecdotal evidence of such a channel of information leakage. For example, Movie Gallery's stock dropped by 25% over the two days following a private

trader at a hedge fund often deals in all of a company's debt instruments. In a situation of this nature, precluding discretionary use of private information and maintaining confidentiality are a challenge.[4]

In fact, both anecdotal evidence and empirical studies indicate that informed trading takes place in the corporate bond market. Following insider trading and price manipulation scandals in corporate bonds in the late 1980s, the opaqueness of this market has become a major concern for regulators.[5] Datta and Iskandar-Datta (1996) argue that in the absence of any reporting requirements for insider bond transactions, insiders have an enhanced opportunity to exploit private information and take advantage of uninformed traders. Consistent with this view, former Securities and Exchange Commission (SEC) chairman Arthur Levitt stated in 1998 that the SEC had "found anecdotal evidence of the possible misuse of inside information in the high-yield [debt] market" (Levitt 1998). Recently, there have also been a few high-profile cases, such as the Delphi and Six Flags debt restructurings, with alleged insider trading in corporate bonds.[6] Furthermore, recent empirical studies on the informativeness of bond trading prior to corporate takeover announcements (Kedia and Zhou 2009) and on holdings in corporate bonds by mutual funds (Manconi and Massa 2009) have found evidence consistent with informed trading in corporate bonds.

Market microstructure theory suggests that information asymmetry among traders affects asset prices. Easley and O'Hara (2004) show that during the process of incorporating new information into prices, the informational advantage of informed traders creates additional risks for uninformed traders. Uninformed traders always end up with portfolios that invest too much in bad assets and too little in good ones. Furthermore, in a world with asymmetric information, the uninformed are unable to diversify this risk of losing to the informed. Therefore, in a nonrevealing equilibrium, lower prices are required for investors to hold securities about which they are uninformed. Several empirical studies have tested this theoretical prediction for the equity market and found that the higher degree of informed trading leads to lower current stock prices, and hence higher returns (e.g., Easley et al. 2002, 2010; Burlacu et al. 2008). One noticeable exception is Duarte and Young (2009), who find that liquidity, rather than information asymmetry, is priced in the cross section of stock returns.

In this paper, we explore the relevance of information asymmetry for corporate bonds by examining the pricing implications of informed bond trading and its power in predicting corporate defaults. First, we test whether corporate bond yield spreads increase with the degree of information asymmetry among traders. Given the coupon rate and principal amount, the value of a corporate bond depends importantly on the risk of default. The theory discussed earlier suggests that the existence of investors who are better informed about the credit risk of a bond creates additional risk for uninformed investors. Therefore, all else being equal, bonds with a higher degree of information asymmetry should have lower prices, or, equivalently, higher yields, in equilibrium to compensate bond investors for taking such information risk.[7] Second, we test whether the degree of information asymmetry among traders may help forecast corporate defaults. A potential channel of such predictability is based on the premise that bonds are generally more information sensitive when the issuer is closer to default (e.g., Gorton and Pennacchi 1990). Indeed, consistent with this view, Wei and Zhou (2012) find that informed trading in corporate bonds is observed mainly in high-yield bonds, especially prior to the issuer's release of negative news (i.e., disappointing earnings announcements). The higher adverse selection risk resulting from the greater degree of informed trading leads to lower overall bond liquidity (Glosten and Harris 1988), making it more costly and difficult for the issuer to refinance its existing debt, resulting in higher default risk (He and Xiong 2012). As such, we expect that the degree of information asymmetry observed in bond trading may help forecast corporate defaults.

In implementing our empirical analysis, we utilize augmented Trade Reporting and Compliance Engine (TRACE) data to estimate two alternative measures of information asymmetry in bond trading, measures

conference call with lenders, most of whom are hedge funds, despite the fact that the firm did not release any news to the public (Anderson 2006).

[4] "You can't put a Chinese wall through someone's head," commented Michael Kaplan from Davis Polk and Wardwell LLP. For further discussions of potential insider trading in the bond market, see Sargent (2005).

[5] In a well-known case in 1989, James Dahl, an employee of Michael Milken's junk bond department, swore before a grand jury that Milken advised him to buy up Caesar's World's bonds from its own customers on the day when Milken made a presentation to Caesar's World on how to handle its finance (Fatsis 1990).

[6] In 2008, Delphi Corporation accused investors of insider trading, alleging that at least one of its 17 institutional investors shorted its bonds after receiving confidential information on the firm's bankruptcy exit financing (McCracken 2008). In 2009, a hedge fund allegedly dumped the low-rated bonds of Six Flags after obtaining information in the process of negotiating the firm's reorganization plan (Spector and McGinty 2010).

[7] Although lower bond price implies higher yields or higher expected returns, yield spreads and expected returns are not identical. Expected returns can be measured by yield spreads corrected for default losses. See de Jong and Driessen (2006) and Campello et al. (2008). We thank an anonymous referee for pointing out this difference.

based on Madhavan et al. (1997) and Glosten and Harris (1988) (hereafter, MRR and GH, respectively). The augmented TRACE data include transaction data used in previous studies, such as the execution date and time, price, and quantity for each trade, as well as information on the trading direction, an indicator for the side of a trade that the reporting party (a dealer) takes.[8] In the absence of quality dealer quote data, knowing the direction of the trades allows us to estimate information-based microstructure measures, a task that was not feasible before.

Our key findings are the following: First, microstructure measures of information asymmetry, even though originally developed for the equity market, seem to capture adverse selection in the corporate bond trading reasonably well. In particular, both of our measures show that information asymmetry is higher in larger sized trades. This result is consistent with the notion that, in contrast with the common practice in the equity market, bond traders do not break orders to minimize price impact because of higher transaction costs for smaller bond trades.

Second, we find strong evidence that information asymmetry in bond trading has significant power in explaining corporate yield spreads even after accounting for the transaction costs of liquidity and other bond pricing factors. Specifically, a one-basis-point increase in the MRR and the GH information asymmetry measures causes the bond's yield spread to increase 0.37 and 0.30 basis points, respectively. This result is robust after controlling for the transaction costs of liquidity, alternative measures of credit risk, firm and time fixed effects, and industry effects, as well as after using an instrumental variable (IV) approach to mitigate the potential influence of endogeneity and unobservable credit risks. We also find stronger information effects for lower rated or shorter term bonds, and for bonds issued by privately held firms.

Finally, the degree of informed trading in bonds helps predict corporate defaults. The predictive power of our asymmetric information measures remains significant, albeit weaker, after we condition on other firm-specific and macroeconomic default prediction variables as used by Duffie et al. (2007). Furthermore, information asymmetry in corporate bond trading seems to be especially useful in forecasting defaults for private firms. This result may reflect the fact that for these firms, the corporate bond market constitutes the only venue for informed traders to exploit their information advantages.

Our main contributions to the literature are the following: First, to the best of our knowledge, this study is the first to measure the degree of information asymmetry in corporate bond trading and examine its implications for corporate bond pricing.[9] Standard bond pricing models, being either structural or reduced form, have had limited success in explaining the observed corporate yield spreads in that empirical applications of these models find that credit risk accounts for only a fraction of yield spreads (e.g., Collin-Dufresne et al. 2001, Huang and Huang 2003).[10] Recent research has started to look beyond these models to understand the credit spread puzzle. For example, studies have shown that information asymmetry between debtors and investors may lead to higher credit spreads. Such information asymmetry may arise because a firm reports its financial data only periodically (Duffie and Lando 2001), accounting information is opaque (Yu 2005), or debtors generally know more than bondholders (Cai et al. 2007). Studies have also found that liquidity affects bond prices significantly through either increased transaction costs (Longstaff et al. 2005, Chen et al. 2007, Bao et al. 2011) or being an additional risk factor (de Jong and Driessen 2006).

This paper contributes to the literature on the credit spread puzzle by highlighting the role of price discovery risks in determining corporate yield spreads. Price discovery and liquidity are two main but different functions of markets (O'Hara 2003). Liquidity refers to the ease of matching buys and sells. When buy and sell orders follow independent stochastic processes without being informative about future price movements, a spread can emerge between buying and selling prices as compensation for providing liquidity.[11] Therefore, strictly speaking, liquidity is not necessarily related to how information gets incorporated into prices, nor to the degree of information asymmetry. It is this liquidity cost dimension of the bond market that has been addressed in previous studies. Our findings suggest that in addition to compensation for liquidity costs, corporate yield spreads may contain an information premium that has not been considered before. Our results support the argument by O'Hara (2003, p. 1335) that "asset pricing models need to be recast in broader terms to incorporate the transaction costs of liquidity *and the risks of price discovery*" (italics added).

Second, our study sheds some light on the decision of public equity listing by examining the effect

[8] The TRACE data analyzed by Edwards et al. (2007) also included information on trade direction, but this information was not made available to the public until very recently.

[9] Related to our study, Odders-White and Ready (2005) show that microstructure measures of adverse selection in equity trading are larger when credit ratings of the issuer's bonds are poor.

[10] See, for example, Merton (1974), Longstaff and Schwartz (1995), Leland and Toft (1996); Collin-Dufresne and Goldstein (2001) for structural models; and Jarrow and Turnbull (1995) and Duffie and Singleton (1999) for reduced-form models.

[11] See O'Hara (1995) for an excellent textbook treatment of liquidity issues in the market microstructure theory.

of information asymmetry among traders on private firms' borrowing costs. Whereas early studies explored the effect of an information environment on a firm's equity or overall values, the direct effect of public status on the cost of debt has received little attention.[12] Furthermore, limited data on private firms render it difficult to empirically evaluate the costs and benefits of being private.[13] Because corporate bonds are publicly traded for both public and private firms, we not only relax the data constraints but also provide additional insights into the benefits of being public. Thus, our study compliments the discussions on the motivation for being public and the relative costs of financing in the public versus private markets (e.g., Modigliani and Miller 1963, Scott 1976).

Finally, our study contributes to the literature on corporate default prediction. Previous studies have explored the predictive power of many firm-specific and macroeconomic variables, including the firm's distance to default and stock return, stock market return, and term structure of interest rate (e.g., Duffie et al. 2007, Bharath and Shumway 2008). However, these studies pay little attention to the information that may be conveyed from corporate bond trading. We find that microstructure measures of information asymmetry exhibit additional power in forecasting corporate defaults after conditioning on traditional default prediction variables. Our results highlight the value of information contained in bond trading activities to gauging a firm's default risk, especially for firms that do not have publicly traded equities.

2. Measuring Information Asymmetry, Liquidity, and Yield Spreads for Corporate Bonds

2.1. Data and Sampling

Compared with the abundant literature on the pricing of equity securities, research on corporate bond pricing is much sparser due in part to the lack of high-quality bond transaction data. Unlike the stock market, the corporate bond market is an opaque dealer market where most securities are traded over the counter (OTC) with little trading information available to the public. In an effort to improve the transparency in the corporate bond market, the Financial Industry Regulatory Authority (FINRA) now requires its members to report all of their secondary corporate bond transactions through its TRACE. FINRA has also phased in real-time reporting of this information to the public. The public dissemination took place on July 1, 2002, first for a small number of selected corporate bonds and then expanded over time to eventually, on February 7, 2005, cover OTC trades of all but Rule 144A corporate bonds.

The augmented TRACE data used in this study include detailed information on each publicly disseminated trade, including the execution date and time (recorded to the second), price, quantity, trade direction indictor, as well as other information that can be used to purge invalid transaction reports. Trades are of three types: customer trade in which the dealer bought from a customer, customer trade in which the dealer sold to a customer, and interdealer trade (with only sell-side reports). We used all but interdealer trades. Following the practice of previous studies using the TRACE data, we removed observations with "data errors"—observations with missing price or quantity values, prices outside the range of 10 to 500, and price reversals over 20% in adjacent trades (e.g., Edwards et al. 2007, Goldstein et al. 2007). In addition, to limit estimation errors, we excluded bond-quarters with fewer than 60 trades in the quarter. We started with a sample consisting of bonds issued by publicly traded firms over the period 2003 to 2008. Information on bond characteristics, such as offering date and amount, maturity, historical credit ratings, and coupon rate, was obtained from the Fixed Income Securities Database (FISD). Issuer accounting information, based on consolidated parent-level reports, was retrieved from the Compustat Annual Industrial Database, whereas trade information on issuer equity and macroeconomic data were obtained from the Center for Research in Security Prices (CRSP) data files. We excluded bond-quarters when either the time since issuance or remaining maturity was shorter than a quarter, and bond-quarters with credit rating changes to better identify the effects of information asymmetry.[14] Applying these filters resulted in a sample of 2,514 bonds by 522 firms.

2.2. Microstructure Measures of Information Asymmetry

We use microstructure models to estimate the degree of information asymmetry. A key insight of the market microstructure literature is that trading by investors possessing superior information on asset values creates an adverse selection risk to market makers. In equilibrium, market makers require extra

[12] For studies on the effect of information environment on firm financing and values, see, for example, Leland and Pyle (1977), Chemmanur and Fulghieri (1999), and Subrahmanyam and Titman (1999).

[13] For studies on the public–private choices, see, for example, Pagano et al. (1998), Kim and Weisbach (2008), and Bharath and Dittmar (2010).

[14] We excluded bonds that were newly issued or close to maturity because trading in these bonds tends to be unusual. See, for example, Goldstein and Hotchkiss (2007) and Cai et al. (2007). Our results hold when using two quarters or one year as the cutoff point.

bid–ask spreads to compensate for taking on such informational risk (e.g., Glosten and Milgrom 1985). Importantly, the effect of adverse selection on asset prices is permanent, as opposed to the transitory effect of the liquidity provision costs—costs normally associated with order processing and inventory risk. A number of studies, including MRR and GH, exploit such distinction and design models to decompose bid–ask spreads into an adverse selection or information asymmetry component and a liquidity provision component. Here we implement GH and MRR models using the augmented TRACE data.[15]

Specifically, the GH model consists of following assumptions:

$$m_t = m_{t-1} + Q_t Z_t + e_t, \tag{1a}$$

$$P_t = m_t + Q_t C_t, \tag{1b}$$

$$Z_t = z_0 + z_1 V_t, \tag{1c}$$

$$C_t = c_0 + c_1 V_t. \tag{1d}$$

The changes in the unobserved "true" price (m_t) can be caused by either the arrival of public information (e_t) or private information embedded in the order flow ($Q_t Z_t$) (Equation (1a)), where Q_t is a trade direction indicator that is $+1$ if the trade is buyer initiated and -1 if the trade is seller initiated, and Z_t is the adverse selection component of the spread (Equation (1c)). The observed price, P_t, is the summation of the unobserved true price and the transitory component of trading costs ($Q_t C_t$) (Equation (1b)), where C_t is the liquidity cost component of the spread (Equation (1d)). Both components are assumed to be a linear function of the size of the order (V_t). Equations (1a)–(1d) are then combined to obtain the following model on observed price changes (ΔP_t):

$$\Delta P_t = z_0 Q_t + z_1(Q_t V_t) + c_0 \Delta Q_t + c_1 \Delta(Q_t V_t) + e_t. \tag{1}$$

We use model (1) to estimate parameters (z_0, z_1, c_0, c_1) and then compute the asymmetric information and transaction cost components as in Equations (1c) and (1d), respectively, with V_t evaluated at the average trade size for each bond-quarter.

Differing from the GH model, MRR assume that only the surprise in the order flow has an impact on the expected fundamental value of the asset; that is, using the same notations as in the GH model, MRR differentiate the transitory effect of liquidity provision costs from the permanent effect of information asymmetry as follows:

$$m_t = m_{t-1} + z\big(Q_t - E[Q_t \mid Q_{t-1}]\big) + e_t, \tag{2a}$$

$$P_t = m_t + cQ_t + \varepsilon_t, \tag{2b}$$

where $\hat{Q}_t \equiv (Q_t - E[Q_t \mid Q_{t-1}])$ measures the surprise in order flows that may carry private information about the fundamental asset value. The parameter z captures the permanent impact of order flow innovations, and hence is used to measure the degree of information asymmetry, whereas c captures the temporary effect of order flow on prices and therefore is used to measure the liquidity provision costs. Similar to the GH model, the changes in transaction prices can be expressed as

$$\Delta P_t = z\hat{Q}_t + c\Delta Q_t + E_t. \tag{2}$$

Following MRR, we assume $E[Q_t \mid Q_{t-1}] = \rho Q_{t-1}$.[16] Thus, $\hat{Q}_t = Q_t - \rho Q_{t-1}$ in our estimations.

One limitation with our TRACE data is that the trade size information disseminated to the public is capped for very large trades. Specifically, the caps for investment- and speculative-grade bonds are \$5 million and \$1 million, respectively. Because we do not observe the actual trade sizes for these large trades, we excluded them in implementing the GH model.[17] However, we included all trades in estimating the MRR model because this model uses only information on trade price and direction. We estimated both the GH and MRR models for each bond-quarter pair. Because bond prices are quoted as a percentage of par, the information asymmetry and liquidity cost components of bid–ask spreads are also expressed as a percentage of par. The estimated GH and MRR information asymmetry measures are highly correlated with each other, with a correlation coefficient of 0.867. Their respective correlations with total number of trades within the quarter are -0.029 and -0.028.

2.3. Estimating Corporate Bond Yield Spreads

The yield spread of a corporate bond is defined as the spread of the yield on the corporate bond over the yield on a default-free bond with exactly the same maturity and coupon. To start, we estimated the daily risk-free zero-coupon yield curve using the extended Nelson–Siegel model, as outlined in the appendix (see also Bliss 1997). Then, for each corporate bond, we discounted its contractual cash flow at the estimated risk-free yield curve to compute the price of a corresponding risk-free bond. Finally, yield on this hypothetic risk-free bond was calculated and subtracted from that on the original corporate bond to obtain its yield spread. We first used this procedure to estimate

[15] See Van Ness et al. (2001) for a review of alternative measures of information asymmetry. Because of the lack of quality bond quote data, models that rely on quote prices cannot be estimated for corporate bonds.

[16] If trade direction changes follow a Markov process with the probability of switching direction from buyer initiated to seller initiated, or vice versa, being the same π, then $\rho = 1 - 2\pi$.

[17] We also estimated the GH model by treating trades with "5MM+" and "1MM+" codes as if their corresponding sizes were \$5,000,000 and \$1,000,000, respectively. The results are qualitatively the same as those reported here. See Table 6 and §4.3.

Table 1 Summary Statistics on Information Asymmetry by Credit Ratings

Panel A: Asymmetric information measures by credit ratings

	AAA and AA		A		BBB		BB and lower	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
MRR AsymInfo (bp)	3.605	1.219	5.388	2.385	7.535	3.308	10.882	7.231
GH AsymInfo (bp)	3.113	1.043	4.766	2.366	6.158	2.993	9.856	6.434
N	1,955		5,985		3,687		4,138	

Panel B: Investment grade vs. high yield

	Investment grade		High yield			
	Mean	Median	Mean	Median	t-test	Wilcoxon test
MRR AsymInfo (bp)	5.550	2.345	10.892	7.231	<0.0001	<0.0001
GH AsymInfo (bp)	4.702	2.195	9.927	6.409	<0.0001	<0.0001
N	11,627		4,138			

Notes. This table shows summary statistics on two alternative information asymmetry measures by credit ratings. *GH AsymInfo* and *MRR AsymInfo* refer to the asymmetric information measures estimated using the Glosten and Harris (1988) and Madhavan et al. (1997) models, respectively. Each information measure is expressed as a percentage of par value. Our sample consists of quarterly observations of 2,514 bonds by 522 public firms over the period 2003–2008, totaling 15,765 bond-quarters. Panel A reports the mean and median values of GH and MRR measures by credit ratings. In panel B, we conduct t-tests and Wilcoxon tests on the differences in, respectively, mean and median values of GH and MRR measures for investment-grade and high-yield bonds, and we report the corresponding p-value for each test. We exclude all bond-quarters with credit rating changes from this calculation. *N* stands for the number of bond-quarters.

each bond's daily yield spread, and then averaged the daily yield spreads within a quarter to get the bond's yield spread for that quarter.

3. Assessing Measures of Information Asymmetry in Corporate Bond Trading

Because information measures, including those derived from the GH and MRR models, were originally developed for the equity market, a natural question is how well they capture the underlying information asymmetry in corporate bond trading. Admittedly, direct assessment of the validity of these measures is extremely difficult, even for equity trading, simply because information asymmetry is never precisely observable. In this section, we try to address the model validation issues indirectly by verifying two key characteristics of these measures as implied by related theories. If these measures are indeed able to capture at least some of the information asymmetry in bond trading, they should exhibit certain patterns consistent with our expectations.

3.1. Information Asymmetry Measures by Credit Ratings

Our first test relates the risk of adverse selection in bond trading to the bond's credit risk.[18] 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. Therefore, any information related to the firm's underlying assets should affect its bond values. However, the relevance of the information for bond traders depends on the moneyness of the option. When the put is deep out of the money (i.e., when the underlying asset value greatly exceeds the strike price, or the face value of bonds), the issuer has a low probability of default, and thus information on asset values is of little relevance. The relevance of the information tends to increase for bond traders when the issuer's credit risk rises.[19] Thus, the degree of informed trading in bonds should be positively related with the bond's credit risk.

Table 1 provides summary statistics by credit ratings on the information asymmetry measures estimated using the GH and MRR models. Panel A shows that, as expected, information asymmetry tends to be higher for lower rated bonds. The mean values of information asymmetry estimates, using either the GH or the MRR model, increase by two times when we move from high-quality investment-grade bonds (rated AAA or AA) to high-yield bonds (rated BB and lower). Panel B presents the results of t-tests and Wilcoxon signed rank tests on the differences in, respectively, the mean and the median of the information asymmetry measures between investment-grade

[18] Several studies have examined the relationship between liquidity and bond credit risks. Ericsson and Renault (2006) argue that illiquidity and credit risk are positively correlated. He and Xiong (2012) show that deteriorating market liquidity and shorter debt maturity can lead to excessive credit risk.

[19] Consistent with this view, Easton et al. (2009) document significant bond price reactions to earnings announcements, and such reactions are stronger when the announcements convey bad news.

and high-yield bonds. The mean (median) of the MRR information asymmetry measure is 10.89 (7.23) basis points for high-yield bonds, but only 5.55 (2.35) basis points for investment-grade bonds. These differences are all statistically significant at the 1% level. Similar results hold for the GH information asymmetry measure.

3.2. Information Asymmetry Measures and Trade Size

Our second test relates information asymmetry in bond trading to trade size. Microstructure theory suggests that informed traders prefer to make large trades to fully exploit their information advantages (e.g., Easley and O'Hara 1987). Therefore, prices for large trades reflect such increased probability of informed trading. However, empirical studies in equity trading do not always support such a prediction. In fact, several papers have found less informed trading in the large equity trades (e.g., Huang and Stoll 1997, Barclay and Warner 1993, Chakravarty 2001). In part, these findings may reflect the strategy of traders to break up large trades and spread them over time to reduce price impact and transaction costs (Kyle 1985).

However, such a strategy might not work for bond traders. A number of empirical studies have shown that transaction costs in corporate bond trading are actually larger for smaller sized trades (Hong and Warga 2000, Schultz 2001, Chakravarty and Sarkar 2003, Warga 2004, Bessembinder et al. 2006, Edwards et al. 2007, Goldstein et al. 2007). Therefore, as predicted by Easley and O'Hara (1987), adverse selection risks should be more severe in large trades of corporate bonds. If the information asymmetry measures derived from the GH and MRR models capture the degree of informed trading, we would expect them to be positively correlated with trade size.

GH explicitly model the information asymmetry component of the bid–ask spread as a function of trade size (see Equation (1c)). Therefore, if larger trades are more likely to be initiated by informed traders, we would expect to see a positive z_1. Panel A of Table 2 provides supporting evidence for this prediction. The estimate of z_1 is a positive 0.007 with a p-value of 0.0377 when large trades subject to TRACE cap are excluded. This estimate is little changed when we treat large trades with "5MM+" and "1MM+" codes as if their sizes were \$5,000,000 and 1,000,000, respectively, and in this case, the p-value drops to 0.0002.

In the original MRR model, the information asymmetry measure does not depend on trade size. However, it is straightforward to extend their model to explicitly account for potential trade size effects. Specifically, we replace the constant effects of information and liquidity, as captured by the coefficients z and c in Equations (2a) and (2b), with functions $f(V_t)$ and $h(V_t)$, respectively. We consider two alternative forms for these functions as follows.

Table 2 Information Asymmetry and Trade Size

Panel A: The coefficient of trade size in the information effect determination equations					
GH model without trades subject to cap		GH model with all trades		Modified MRR model (2′)	
Estimate	p-value	Estimate	p-value	Estimate	p-value
0.007	0.0377	0.007	0.0002	0.0188	<0.0001

Panel B: Information asymmetry by trade size						
	Large trades		Medium		Small	
	Mean	Median	Mean	Median	Mean	Median
Estimate	0.035083	0.023081	0.013611	0.006613	0.015227	0.008466
p-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
	Large vs. medium		Large vs. small		Medium vs. small	
	t-test	Wilcoxon test	t-test	Wilcoxon test	t-test	Wilcoxon test
p-value	<0.0001	<0.0001	<0.0001	<0.0001	0.6078	0.2379

Notes. This table analyzes the effect of trade size on the degree of information asymmetry in bond trading. In panel A, the coefficient for trade size in determining the information component of bid-ask spread—i.e., z_1 in Equation (1c) of the GH model—is estimated both with and without large trades that are subject to TRACE cap. We also modified the MRR model to account for a linear size effect and showed the estimated coefficient of trade size, α_1 in Equation (2′a). In panel B, we further modified the MRR model to account for a potential nonlinear size effect, and estimated the information effect for large, medium, and small bond trades separately. For a bond-quarter to be included in this analysis, we impose the restriction that there are at least 20 trades in each size category, with in total at least 60 trades as discussed in the data description section. The mean and median values (together with their p-values) are presented for the coefficients z^s, z^m, and z^l in Equation (2″a). We also conduct t-tests and Wilcoxon tests for each pairwise comparison of these coefficients for different trade size groups, and present the corresponding p-values in the bottom part of panel B.

First, we assume that, as in GH, both information and liquidity impacts are linear in trade size:

$$f(V_t) = \alpha_0 + \alpha_1 V_t, \tag{2'a}$$

$$h(V_t) = \beta_0 + \beta_1 V_t. \tag{2'b}$$

Therefore, replacing z and c with $f(V_t)$ and $h(V_t)$ in Equation (2) yields

$$\Delta P_t = \alpha_0 \hat{Q}_t + \alpha_1 (V_t \hat{Q}_t) + \beta_0 \Delta Q_t + \beta_1 \Delta(V_t Q_t) + E_t. \tag{2'}$$

Panel A of Table 2 shows that the information component estimated using the modified MRR model is again positively correlated with trade size, with α_1 being 0.019 and significant at the 1% level.

Second, we consider a more general case that allows for potential nonlinear effects of trade size in the MRR model. To do so, we create three size dummy variables, D^s, D^m, and D^l for small, medium, and large trades, respectively. We classify trades with par values less than \$100,000 as small trades, those with par values of at least \$1 million as large trades, and those in between as medium size trades. Notice that this classification also allows us to include all large trades that are subject to the TRACE cap without assigning any fixed number (\$5 million or \$1 million). Thus, the information and liquidity effects can be expressed as

$$f(V_t) = \sum_{k=s,m,l} z^k D_t^k, \tag{2''a}$$

$$h(V_t) = \sum_{k=s,m,l} c^k D_t^k. \tag{2''b}$$

Replacing z and c with $f(V_t)$ and $h(V_t)$ in Equation (2) now gives

$$\Delta P_t = \sum_{k=s,m,l} z^k (D_t^k \hat{Q}_t) + \sum_{k=s,m,l} c^k (D_t^k Q_t) + E_t. \tag{2''}$$

As shown in panel B, for each size group, both the mean and the median values of the information effect (as captured by z) are positive and significant at the 1% level. More importantly, both the t-test and the Wilcoxon test indicate that the z estimate for the large trades is greater than that for the medium and the small trades, but that there is no significant difference in the z estimates between medium and small trades. This result again confirms that, consistent with the theoretical prediction of Easley and O'Hara (1987), larger bond trades tend to be more informative in the bond market.

We also find that, in contrast to information asymmetry, liquidity costs tend to be larger for smaller trades (results are not shown but available upon request), a finding consistent with aforementioned studies on corporate bond transaction costs. Additionally, we explored how liquidity provision is related to information asymmetry in the bond market. We find that when bond liquidity is relatively high, information asymmetry decreases as liquidity decreases, suggesting that at least some of the liquidity is provided by potentially informed dealers, a conclusion also reached by Qiu and Yu (2010) for the credit default swap (CDS) market. However, when liquidity is further decreased to the lowest level, information asymmetry experiences a significant increase. This finding indicates the existence of potentially informed trading by traders other than potentially informed dealers.

4. Information Asymmetry and Corporate Yield Spreads

We now examine whether our estimated information asymmetry measures possess any explanatory power for corporate yield spreads after controlling for factors considered in standard corporate bond pricing models. As discussed previously, market microstructure theory suggests that investors would require higher yields to hold those bonds that exhibit more asymmetric information risk, above and beyond the yield compensation for credit risk and liquidity cost. Therefore, our hypothesis is that corporate yield spreads are positively related to information asymmetry measures.

4.1. The Effect of Information Asymmetry on Corporate Yield Spreads

Our strategy is to incorporate our information asymmetry measures into existing empirical models for corporate yield spreads (see, e.g., Campbell and Taksler 2003, Chen et al. 2007). These models are often motivated by a structural view of corporate default, which holds that a firm's credit risk, in terms of both the probability of default and losses given default, depends on its capital structure and the firm value. Various firm accounting variables and macroeconomic variables have been used as proxies for a firm's credit risk. In addition, bond-specific characteristics and proxies for liquidity conditions have also been used as determinants of bond yield spreads. Consistent with this literature, we specify our empirical model as follows:

$$\begin{aligned} &\mathit{YieldSpread}_{i,t} \\ &\quad = \gamma_0 + \gamma_1 \mathit{AsymInfo}_{i,t} + \gamma_2 \mathit{Liquidity}_{i,t} + \gamma_3 \mathit{Rating}_{i,t} \\ &\qquad + \gamma_4 \mathit{Maturity}_{i,t} + \gamma_5 \mathit{Age}_{i,t} + \gamma_6 \mathit{IssueSize}_{i,t} \\ &\qquad + \gamma_7 \mathit{Coupon}_{i,t} + \gamma_8 \mathit{1yrTreasuryRate}_t \\ &\qquad + \gamma_9 (\mathit{10yr\text{–}2yrTreasuryRate}_t) + \gamma_{10} \mathit{EuroDollar}_t \\ &\qquad + \gamma_{11} \mathit{Long\text{-}TermDebt/TotalAssets}_{i,t} \\ &\qquad + \gamma_{12} \mathit{TotalDebt/Capitalization}_{i,t} \\ &\qquad + \gamma_{13} \mathit{OperatingIncome/Sales}_{i,t} \\ &\qquad + \gamma_{14} \mathit{PretaxInterestCoverage}_{i,t} \end{aligned}$$

Table 3 Information Asymmetry and Corporate Yield Spreads

	Panel A: Using MRR asymmetry information measure				Panel B: Using GH asymmetry information measure			
	I		II		III		IV	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
AsymInfo	0.373	0.000	0.311	0.000	0.297	0.000	0.281	0.000
Liquidity	0.508	0.000	0.241	0.000	0.478	0.000	0.230	0.000
Rating	0.398	0.000	0.604	0.000	0.390	0.000	0.602	0.000
Maturity	−0.070	0.000	−0.031	0.000	−0.069	0.000	−0.031	0.000
Age	−0.019	0.002	−0.009	0.082	−0.015	0.015	−0.008	0.136
IssueSize	0.086	0.006	−0.207	0.000	0.083	0.008	−0.211	0.000
Coupon	0.558	0.000	0.335	0.000	0.558	0.000	0.335	0.000
OI/Sales	−0.001	0.851	−0.003	0.481	−0.001	0.864	−0.002	0.518
PretaxInterestCoverage	0.000	0.975	−0.003	0.044	0.000	0.988	−0.003	0.044
LTD/TA	−0.138	0.320	0.051	0.844	−0.172	0.215	0.050	0.848
TD/TC	1.907	0.000	2.032	0.000	1.974	0.000	2.030	0.000
IssuerStockVolatility	76.095	0.000	75.419	0.000	75.817	0.000	75.592	0.000
IssuerStockReturn	−50.186	0.000	−35.739	0.000	−50.578	0.000	−36.041	0.000
1yrTreasuryRate	−0.491	0.000	−0.551	0.000	−0.488	0.000	−0.549	0.000
10yr−2yrTreasuryRate	−0.732	0.000	−0.768	0.000	−0.726	0.000	−0.765	0.000
EuroDollar	0.435	0.000	0.497	0.000	0.453	0.000	0.500	0.000
StockMarketReturn	−24.749	0.238	−30.983	0.134	−25.852	0.218	−31.281	0.130
StockMarketVolatility	20.352	0.004	27.142	0.000	20.256	0.004	26.952	0.000
Adj. R^2	0.662		0.771		0.661		0.771	
N	15,160		15,160		15,160		15,160	
Firm fixed effect	No		Yes		Yes		Yes	

Notes. This table analyzes the effect of information asymmetry on corporate yield spreads. We estimate model (3) with information and liquidity measures from both the GH and MRR models, and the results are presented in panels A and B, respectively. In each panel, we show results both with and without controlling for the issuer fixed effects. Other explanatory variables include bond characteristics (such as credit rating (*Rating*), term to maturity (*Maturity*), number of years since issuance (*Age*), the log of the total amount of par at issuance (*IssueSize*), and coupon rate (*Coupon*)), firm characteristics (such as long-term debt/total assets (*LTD/TA*), total debt/total capitalization (*TD/TC*), operating income/sales (*OI/Sales*) and pretax interest coverage (*PretaxInterestCoverage*)), macroeconomic variables (the 1-year Treasury rate, the difference between 10-year and 2-year Treasury rates, and the difference between the 30-day Eurodollar and Treasury yields (*EuroDollar*)), the mean and standard deviation of the daily excess return of the issuer's equity (*IssuerStockReturn* and *IssuerStockVolatility*), and the mean and standard deviation of the daily stock market returns (*StockMarketReturn* and *StockMarketVolatility*) in each quarter. Standard errors are corrected for potential correlations across bonds and over time following Thompson (2012). Adj. R^2 and *N* refer to the adjusted R^2 and sample size, respectively.

$$+\gamma_{15}\, IssuerStockVolatility_{i,t} + \gamma_{16}\, IssuerStockReturn_{i,t} + \gamma_{17}\, StockMarketVolatility_t + \gamma_{18}\, StockMarketReturn_t + \varepsilon_{i,t}, \tag{3}$$

where $AsymInfo_{i,t}$ and $Liquidity_{i,t}$ refer to, respectively, the asymmetric information and liquidity cost components of the bid–ask spreads estimated by either the MRR or GH model for bond i in quarter t. The rest of the control variables include bond-specific characteristics (credit rating (*Rating*), time to maturity (*Maturity*), time since issuance (*Age*), coupon rate (*Coupon*), and (log) issue size (*IssueSize*)); firm-specific characteristics (*Long-TermDebt/TotalAssets*, *TotalDebt/TotalCapitalization*, *OperatingIncome/Sales*, and *PretaxInterestCoverage*, and the mean and the standard deviation of the daily excess return of the issuer equity relative to the CRSP value-weighted index (*IssuerStockReturn* and *IssuerStockVolatility*)); and macroeconomic variables (the 1-year Treasury rate (*1yrTreasuryRate*), the difference between 10-year and 2-year Treasury rates ($10yr - 2yrTreasuryRate$), the difference between the 30-day Eurodollar and Treasury yields (*EuroDollar*), and the mean and the standard deviation of the daily stock market returns (measured using CRSP value-weighted index returns) within each quarter (*StockMarketReturn* and *StockMarketVolatility*)).[20]

Table 3 presents regression results based on two specifications of model (3) for each information asymmetry measure. Because our sample contains multiple bonds issued by the same firm over multiple periods, we correct the standard errors following Thompson (2012) to account for potential correlations across bonds and over time. The regression results are presented in columns I and III for MRR and GH measures, respectively. There is strong evidence

[20] We follow the existing literature in defining our control variables. For credit rating, we assign a numeric value to each S&P rating letter, with $1, 2, \ldots, 10$ denoting AAA, AA, …, D, respectively. Firm-specific variables are calculated using Compustat data as of the end of the previous calendar year except for when computing the total debt/total capitalization ratio, where we use the market value of the equity from CRSP and the book value of debt from Compustat to calculate total firm capitalization. See Collin-Dufresne et al. (2001), Elton et al. (2001), Campbell and Taksler (2003), and Chen et al. (2007).

that corporate bond yield spreads reflect information risk. After controlling for liquidity costs, bond- and firm-specific characteristics, and macroeconomic factors, the coefficients of our information asymmetry measures (based on both MRR and GH models) are positive and statistically significant at the 1% level. The point estimate using the MRR (GH) model implies that a one-basis-point increase in the information asymmetry measure leads to a widening of the yield spread by 0.37 (0.30) basis point. To examine the additional power of information asymmetry in explaining yield spreads, we also estimate model (3) without the MRR and GH measures (results not shown). We find that the adjusted R^2 increases by about three percentage points when either MRR or GH measure is included in the estimation. Notice that this incremental explanatory power from the MRR/GH measures is achieved after we control for general liquidity effects, which may have already captured some of the influences from information asymmetry. Furthermore, our results continue to hold when we add firm fixed effects in our model, as shown in columns II and IV. Controlling for firm fixed effects is desirable because bond issues may be concentrated in a small set of firms. The fixed effect model also mitigates the effect of potential unobservable firm heterogeneity on our estimation, effectively allowing us to identify the informational risk effect by comparing bonds issued by the same firm. As we can see, the coefficients of information asymmetry measures continue to be positive and statistically significant, and their magnitudes are only slightly lower.

Consistent with findings in previous studies on liquidity effects, the coefficients for liquidity provision costs are also positive and significant at the 1% level. A one-basis-point increase in the MRR (GH) liquidity cost measure is accompanied with a 0.51 (0.48) basis point increase in yield spread. Note that some bond-specific characteristics, such as issue size, coupon rate, and age, have also been used extensively in the literature as proxies for bond liquidity, especially before the TRACE data became available.[21] Our results on these variables are also largely consistent with findings in existing studies.

Furthermore, the coefficients of other control variables carry expected signs and are generally consistent with previous studies. For example, both the level and the slope of term structure, which are indicators of economic expansions, carry a significant, negative sign, suggesting that yield spreads widen during economic downturns. The coefficient for Eurodollar, which measures market liquidity effects on corporate bonds relative to Treasury bonds, is positive and statistically significant, as expected. In addition, lower total debt ratios and higher pretax interest coverage are associated with lower yield spreads, suggesting that financially healthy firms incur lower costs of debt. Finally, greater equity volatility is associated with higher yield spread, consistent with Campbell and Taksler (2003).

4.2. Alternative Controls for Credit Risks

The interpretation of our results relies importantly on appropriate control for credit risk, because, to the extent that unobserved credit risk may be positively correlated with information asymmetry in bond trading, inadequate control for credit risk may result in a bias favoring finding positive information effects. In this section, we took the following two alternative approaches to control for the potential confounding effect of credit risk: First, we experimented with alternative specifications of bond credit ratings, as well as some structurally generated nonlinear variables, in addition to traditional accounting and market-based ratios, as proxy for credit risks. Second, we used an IV approach to mitigate the effect of unobservable heterogeneity in credit risk.

The results based on our first approach using the MRR information asymmetry measure are presented in Table 4. Using the GH measure yields similar results which, because of limited space, are not reported but available upon request. Under this approach, we have done the following experiments.

First, we considered two alternative methods to control for bond credit ratings. One, we refined the credit rating variable by using notch-level ratings (compared with letter-level ratings mentioned previously) from Standard and Poor's (S&P).[22] A more granular rating variable may control for more variation in the credit risk. As shown in column I of Table 4, the coefficient of the information asymmetry measures is positive and statistically significant at the 1% level. In fact, its magnitude barely changes from that found when using the letter-level ratings (see column II of Table 3). Two, to account for a potential nonlinear effect from credit rating, we replaced the linear rating variable with six categorical dummy variables for the following rating classes: AAA, AA, A, BBB, BB, and B and lower. Not surprisingly, higher rated bonds tend to have lower yield spreads (see column II). But, more importantly, using rating dummies to control for

[21] See, for example, Gehr and Martell (1992), Alexander et al. (2000), and Hong and Warga (2000). Elton et al. (2004) argue that higher coupon bonds should have higher yield spreads as interest payments on corporate bonds are taxed at the state level.

[22] A numeric value is assigned to each notch of S&P's credit rating, with 1, 2, 3,... denoting AAA+, AAA, AAA−,..., respectively. Notice that the sample for this test shrank a bit as we excluded any bond-quarter when a bond experienced even a single notch of credit rating change.

Table 4 Alternative Controls for Credit Risks

	I. Fine credit rating		II. Credit rating dummy		III. Merton DtoD		IV. Default probability		V. CDS	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
AsymInfo	0.314	0.000	0.308	0.000	0.500	0.000	0.349	0.000	0.249	0.000
Liquidity	0.253	0.000	0.235	0.000	0.401	0.000	0.294	0.000	0.336	0.000
Rating	0.079	0.000								
AAAdum			−3.151	0.000	−3.617	0.000	−3.636	0.000	−1.857	0.000
AAdum			−3.495	0.000	−4.283	0.000	−4.012	0.000	−2.101	0.000
Adum			−3.498	0.000	−4.293	0.000	−4.010	0.000	−2.111	0.000
BBBdum			−3.299	0.000	−4.023	0.000	−3.621	0.000	−1.962	0.000
BBdum			−1.655	0.000	−2.211	0.000	−2.647	0.000	−1.317	0.000
Bdum			−1.330	0.000	−1.539	0.000	−1.918	0.000	−0.715	0.000
DtoD					−0.022	0.002				
DefaultProb							6.236	0.000		
CDSSpread									0.003	0.000
Maturity	−0.031	0.000	−0.032	0.000	−0.045	0.000	−0.037	0.000	−0.032	0.000
Age	−0.009	0.099	−0.013	0.011	−0.015	0.015	−0.010	0.060	−0.019	0.002
IssueSize	−0.189	0.000	−0.161	0.000	−0.090	0.004	−0.093	0.001	0.000	0.999
Coupon	0.349	0.000	0.339	0.000	0.331	0.000	0.341	0.000	0.299	0.000
OI/Sales	0.000	0.980	−0.002	0.601	−0.002	0.582	−0.001	0.885	0.002	0.471
PretaxInterestCoverage	−0.003	0.029	−0.003	0.021	−0.004	0.003	−0.003	0.020	−0.003	0.445
LTD/TA	0.405	0.118	0.213	0.412					−1.378	0.000
TD/TC	2.722	0.000	1.771	0.000					3.669	0.000
IssuerStockVolatility	76.270	0.000	74.239	0.000					46.476	0.000
IssuerStockReturn	−45.130	0.000	−35.835	0.000	−41.659	0.000	−16.580	0.001	−8.312	0.151
1yrTreasuryRate	−0.498	0.000	−0.581	0.000	−0.725	0.000	−0.600	0.000	−0.348	0.000
10yr− 2yrTreasuryRate	−0.731	0.000	−0.797	0.000	−0.925	0.000	−0.736	0.000	−0.458	0.000
EuroDollar	0.453	0.000	0.470	0.000	0.734	0.000	0.653	0.000	0.609	0.000
StockMarketReturn	−29.373	0.157	−36.559	0.074	−73.543	0.002	−64.617	0.002	−0.192	0.993
StockMarketVolatility	31.105	0.000	29.353	0.000	58.179	0.000	41.911	0.000	10.110	0.038
Adj. R^2	0.770		0.776		0.734		0.789		0.840	
N	14,334		15,160		13,889		13,889		6,872	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	

Notes. This table examines five alternative specifications of model (3) to control for potential confounding effect of credit risks. In column I, we use notch-level ratings from S&P to construct the *Rating* variable. A numeric value is assigned to each notch of S&P's credit rating, with 1, 2, 3, ... denoting AAA+, AAA, AAA−, ..., respectively. In column II, we replace the linear rating variable with six categorical dummy variables for the following rating classess: AAA, AA, A, BBB, BB, and B and lower. In column III, we follow Duffie et al. (2007) to construct the distance to default measure based on the Black–Scholes–Merton specification, and then combine this measure with rating dummies to control for credit risk. In column IV, we estimate the conditional default probability based on these distance to default measures, and use it as an alternative control for credit risk. In column V, we use a firm's five-year CDS spread, in addition to credit rating dummies, to control for credit risk. Other explanatory variables include bond characteristics (such as credit rating (*Rating*), term to maturity (*Maturity*), number of years since issuance (*Age*), the log of the total amount of par at issuance (*IssueSize*), and coupon rate (*Coupon*)), firm characteristics (such as long-term debt/total assets (*LTD/TA*), total debt/total capitalization (*TD/TC*), operating income/sales (*OI/Sales*) and pretax interest coverage (*PretaxInterestCoverage*)), macroeconomic variables (the 1-year Treasury rate, the difference between 10-year and 2-year Treasury rates, and the difference between the 30-day Eurodollar and Treasury yields (*EuroDollar*)), the mean and standard deviation of the daily excess return of the issuer's equity (*IssuerStockReturn* and *IssuerStockVolatility*), and the mean and standard deviation of the daily stock market returns (*StockMarketReturn* and *StockMarketVolatility*) in each quarter. Adj. R^2 and N refer to the adjusted R^2 and sample size, respectively.

nonlinearities has little effect on the estimated coefficient of information asymmetry.

Second, we estimated a distance to default (*DtoD*) measure and combined it with rating dummies to control for credit risk. Roughly speaking, the distance to default is the number of standard deviations of quarterly asset growth by which asset values exceed the firm's liabilities. In standard structural models, models that assume a firm defaults when its assets drop to a sufficiently low level relative to its liabilities, the conditional default probability depends heavily (or completely for some models) on the distance to default (e.g., Black and Scholes 1973, Merton 1974). Empirically, the relevance of distance to default in predicting defaults has also been well established in the literature (e.g., Bharath and Shumway 2008, Campbell et al. 2011). Besides its structural and nonlinear nature, the distance to default incorporates current market information more timely than possibly stale credit ratings.

Following Duffie et al. (2007), we constructed our distance to default measure based on the Black–Scholes–Merton specification and used an iterative method to estimate the measure based on market equity data and Compustat balance sheet data (Black and Scholes 1973, Merton 1974). Because the distance to default measure is essentially a volatility-adjusted leverage measure, we excluded firm leverage measures and stock volatility measures as control variables in estimating model (3). Column III in Table 4 shows that the coefficient of the information asymmetry measure remains positive and statistically significant. The coefficient of the distance to default measure is negative and highly significant, consistent with our expectation that bonds issued by firms far from default tend to have lower yield spreads.

The Black–Scholes–Merton specification implies that the conditional default probability is simply the cumulative standard normal distribution function valued at the negative distance to default (see, e.g., Crosbie and Bohn 2002, Vassalou and Xing 2004). So we also use this estimated conditional default probability as an alternative control for credit risk. As shown in column IV of Table 4, the coefficient of default probability is positive and significant, suggesting that yield spreads tend to be wider when the default probability of the issuer increases. Again, information asymmetry continues to exhibit significant explanatory power for corporate yield spreads after controlling for credit risks.

Last, we use a firm's five-year CDS spread, in addition to credit rating dummies, to control for credit risk. CDS spreads are insurance contracts to protect investors against the issuer's default risk. Thus, CDS spreads are generally viewed as a more direct measure for credit risk (see, e.g., Longstaff et al. 2005).[23] In contrast to credit ratings, which are commonly viewed as lagging behind the actual changes in a firm's credit risk, CDS spreads reflect more timely investors' expectations on a firm's credit risk because CDS spreads are market based. We obtain the data on CDS spreads from Markit. Note that our sample size drops by over one half in this test because for many firms, most of which are small, Markit did not receive enough quotes to reliably calculate their CDS spreads. Nevertheless, the results for this reduced sample, which are presented in column V of Table 4, once again confirm the robustness of our main results to using CDS spreads as the alternative credit risk control.

Our second approach for the robustness check is to use an IV method to control for potential endogeneity between information asymmetry and credit risks as well as for unobservable credit risk. A valid IV has to meet the exclusivity condition that the IV is correlated with the measures of information asymmetry, but not directly with a bond's credit risk. Our candidate for the IV, the degree of concentration in institutional ownership of corporate bonds, meets such a requirement, especially when we focus on active institutions such as mutual funds. Several studies have used institutional ownership as a proxy for private information (e.g., Brennan and Subrahmanyam 1995). Thus, for the bonds held by mutual funds, if the holding is highly concentrated in a few funds, the information asymmetry among these active traders may be greater.

We used information on the fund-level institutional holdings of corporate bonds from Lipper's eMAXX fixed income database to estimate the degree of concentration in institutional ownership. This database provides quarterly bond ownership information by all insurance companies, over 95% of mutual funds, and the top 250 public pension funds in the United States.[24] Because insurance companies and pension funds generally face regulatory limitations or investor restrictions on their investments in high-yield bonds, we focused on holdings by mutual funds so that our bond ownership measure is not directly related to credit risks. In addition, unlike mutual funds, most insurance companies and pension funds are "buy-and-hold" investors in the corporate bonds. Therefore, for this market, the risks of losing to more informed traders, as modeled by Easley and O'Hara (2004), are presented mainly by mutual fund trading. With this in mind, for each bond-quarter, we calculated the Herfindahl index in mutual fund holdings, which is the sum of the squared share of each fund in the total amount of bonds held by all mutual funds, as a proxy for concentration among these mutual funds.

On average, our sample bonds are held by 28 mutual funds. The Herfindahl index has a mean value of 0.37, but exhibits high variation across bonds (with a standard deviation of 0.24). Importantly, the Henfindahl index is not higher for lower rated bonds. In fact, the mean (median) value of the Herfindahl index is 0.309 (0.228) for high-yield bonds, which is smaller than 0.395 (0.331), the mean (median) for investment-grade bonds. This finding alleviates the concern that our IV simply captures some unobserved credit risk information.

Table 5 presents the four results estimated using two-stage least squares (2SLS) regressions. In the first stage, we regressed the measures of information asymmetry from the MRR or GH models on the Herfindahl index in bond holding, *Herf*, and all other control variables used in model (3). Panel A shows that the coefficient of the Herfindahl index

[23] CDS spreads may also be affected by their own liquidity issues. Bongaerts et al. (2011) find that the effect of liquidity is statistically significant in the CDS market, but that the magnitude of the effect is rather small. This small magnitude is consistent with the view of Longstaff et al. (2005) that liquidity concerns may be less severe in the CDS market due to the contractual nature of CDS. See also Tang and Yan (2007).

[24] A few other recent studies, for example, Manconi and Massa (2009) and Massa et al. (2008), also used this data set.

Table 5 Two-Stage Least Squares Regression Analysis on Information Effects

	Panel A: First stage results				Panel B: Second stage results			
	I. MRR		II. GH		III. MRR		IV. GH	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	−0.017	0.681	0.001	0.987	−3.514	< 0.0001	−3.579	< 0.0001
Herf	0.093	< 0.0001	0.069	< 0.0001				
AsymInfo					3.284	0.000	4.334	0.000
Liquidity	−0.060	< 0.0001	−0.038	< 0.0001	0.559	< 0.0001	0.514	< 0.0001
Rating	0.017	< 0.0001	0.015	< 0.0001	0.362	< 0.0001	0.347	< 0.0001
Maturity	0.005	< 0.0001	0.004	< 0.0001	−0.082	< 0.0001	−0.083	< 0.0001
Age	0.003	0.000	0.002	0.020	−0.028	0.000	−0.022	0.003
IssueSize	−0.037	< 0.0001	−0.031	< 0.0001	0.302	< 0.0001	0.325	< 0.0001
Coupon	0.005	0.004	0.004	0.016	0.564	< 0.0001	0.565	< 0.0001
OI/Sales	0.001	0.401	0.000	0.654	−0.005	0.284	−0.004	0.391
PretaxInterestCoverage	0.000	0.828	0.000	0.682	0.000	0.988	0.000	0.940
LTD/TA	−0.040	0.027	−0.019	0.234	0.162	0.213	0.107	0.419
TD/TC	0.032	0.061	0.013	0.377	1.586	< 0.0001	1.651	< 0.0001
IssuerStockVolatility	2.405	< 0.0001	1.924	< 0.0001	72.117	< 0.0001	71.269	< 0.0001
IssuerStockReturn	−4.693	< 0.0001	−3.854	< 0.0001	−36.587	< 0.0001	−34.940	< 0.0001
1yrTreasuryRate	−0.023	0.004	−0.021	0.003	−0.412	< 0.0001	−0.391	< 0.0001
10yr− 2yrTreasuryRate	−0.025	0.052	−0.023	0.043	−0.582	< 0.0001	−0.556	< 0.0001
EuroDollar	0.016	0.064	0.015	0.061	0.424	< 0.0001	0.420	< 0.0001
StockMarketReturn	1.067	0.785	1.330	0.698	−33.278	0.225	−36.384	0.202
StockMarketVolatility	4.596	< 0.0001	3.335	< 0.0001	5.324	0.445	5.271	0.465
Adj. R^2	0.074		0.061		0.624		0.606	
N	13,803		13,803		13,803		13,803	

Notes. This table reports the results of IV estimations based on the two-stage least squares regression method. The results from the first stage and second stage regressions are presented in panels A and B, respectively. In the first stage, the dependent variable (*AsymInfo*) is the asymmetry information measure estimated using either the MRR or GH model. In the second stage, the dependent variable is yield spread. Our IV is the degree of concentration in institutional ownership, measured by the Herfindahl index in mutual fund holdings (*Herf*). This variable is estimated using information on the fund-level institutional holdings of corporate bonds from Lipper's eMAXX fixed income database. *Liquidity* refers to the MRR liquidity cost measure. Other explanatory variables include bond characteristics (such as credit rating (*Rating*), term to maturity (*Maturity*), number of years since issuance (*Age*), the log of the total amount of par at issuance (*IssueSize*), and coupon rate (*Coupon*)), firm characteristics (such as long-term debt/total assets (*LTD/TA*), total debt/total capitalization (*TD/TC*), operating income/sales (*OI/Sales*) and pretax interest coverage (*PretaxInterestCoverage*)), macroeconomic variables (the 1-year Treasury rate, the difference between 10-year and 2-year Treasury rates, and the difference between the 30-day Eurodollar and Treasury yields (*EuroDollar*)), the mean and standard deviation of the daily excess return of the issuer's equity (*IssuerStockReturn* and *IssuerStockVolatility*), and the mean and standard deviation of the daily stock market returns (*StockMarketReturn* and *StockMarketVolatility*) in each quarter. Adj. R^2 and N refer to the adjusted R^2 and sample size, respectively.

is positive and highly significant. This result is consistent with our expectation that bonds held by competitive institutions have lower information asymmetry. The results of the second stage regressions, in which we essentially replaced the measures of information asymmetry with their predicted values from the corresponding first stage regressions, are presented in panel B. Consistent with our previous analysis, the coefficients of the information asymmetry measure are all positive and statistically significant at the 1% level.

4.3. Additional Robustness Checks

We conducted a number of additional tests to check the robustness of our results and presented them in Table 6. Note that because of the limited space and to help focus on key results, we show the coefficients on only the information and liquidity measures, but those on other variables are available upon request.

First, we examined whether our results hold when we reestimated our model (3) using alternative estimates of the information and liquidity components. We considered the following three alternative estimates: (a) estimates based on the GH model by treating large trades with "5MM+" and "1MM+" codes as if their trade sizes were \$5,000,000 and \$1,000,000, respectively; (b) estimates based on a modified MRR model allowing the trade effects to be linear in trade size (i.e., model (2′)); and (c) estimates based on a modified MRR model allowing the trade effects to be nonlinear in trade size (i.e., model (2″)). As shown in panel A, in all three cases, the coefficients of the information asymmetry measures continue to be positive and statistically significant at the 1% level.

Second, we checked whether our results are robust to alternative measures of liquidity costs. For this purpose, we reestimated model (3) by replacing the liquidity cost components from the MRR or GH models with several general liquidity measures estimated from unsigned bond transaction data, such as turnover (trade volume normalized by issue size), price impact (Amihud 2002 measure), and trading frequency (both in terms of the number of days traded

Table 6 Robustness Checks

	Panel A: Alternative information measures						Panel B: General liquidity measures										Panel C:		Panel D:		Panel E:	
	I. GH with all trades		II. Modified MRR model (2′)		III. Modified MRR model (2″)		IV. *Turnover*		V. *NTrades*		VI. *NDays*		VII. *Amihud*		VIII. *PriceRange*		Industry effects		Time fixed effects		WLS	
	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.
AsymInfo	0.324	0.000	0.318	0.000	0.594	0.000	0.206	0.000	0.207	0.000	0.205	0.000	0.223	0.000	0.217	0.000	0.307	0.000	0.289	0.000	0.311	< 0.0001
Liquidity	0.213	0.000	0.212	0.000	0.397	0.000	−0.452	0.000	−0.000	0.001	−0.004	0.017	12.206	0.000	0.065	0.000	0.248	0.000	0.224	0.000	0.241	< 0.0001
Control variables	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Firm fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Adj. R^2	0.777		0.777		0.777		0.769		0.769		0.769		0.779		0.769		0.803		0.776		0.771	
N	15,160		15,160		15,160		15,160		15,160		15,160		13,710		15,160		8,915		15,160		15,160	

Notes. This table provides robustness checks of our results on the effect of information asymmetry on corporate yield spreads. In panel A, we reestimate model (3) using three alternative estimates of information measures, including the GH estimates from using all trades, and the extended MRR models with both linear and nonlinear size effects as in models (2′) and (2″), respectively. In panel B, we show the regression results of model (3) using five broad liquidity measures estimated from our bond transaction data, including *Turnover*, number of trades (*NTrades*), number of days traded (*NDays*), the Amihud (2002) illiquidity measure (*Amihud*), and the intraday price range (*PriceRange*). In panel C, we control for potential industry fixed effects by excluding bonds issued by firms in financial or utility industries. In panel D, we estimate a flexible specification of model (3) by replacing macroeconomic variables with year-quarter fixed effects. In panel E, we take the inverse variance of the errors of the corresponding information asymmetry estimations for each bond-quarter as the weight to reestimate model (3) using a WLS approach. All tests are conducted using issuer fixed effect regressions. All control variables of model (3) are included in the estimation, but their coefficients are not reported in the table for the sake of brevity. Adj. R^2 and N refer to the adjusted R^2 and sample size, respectively.

and the number of trades).[25] We also considered intraday price range, which is the difference between the highest and the lowest transaction prices within a day. As a liquidity proxy, intraday price range is in the same spirit as both the realized bid–ask spread proposed by Chakravarty and Sarkar (2003) and the volatility measure proposed by Alexander et al. (2000) and Hong and Warga (2000).[26]

The results using the information asymmetry measure based on the original MRR model are presented in panel B. (Results from using the GH measure are similar and not reported here, but available upon request.) All liquidity measures exhibit expected signs and are statistically significant at the 1% level. Importantly, regardless of which liquidity measure is used, the coefficients of the information asymmetry measures are all positive and statistically significant at the 1% level. Note that the magnitude of these coefficients does drop somewhat. The weaker informational effects are not surprising because these conventional liquidity measures tend to be broadly defined and may capture part of the effects from information asymmetry. For example, the Amihud (2002) measure, which estimates the impact of order flow on price based on Kyle's (1985) λ coefficient, may reflect both adverse selection costs and inventory costs. Also, Goldstein et al. (2007) attribute the cost differences between large and small bond trades to either a high level of fixed costs for small trades or a rent extracted by dealers in trading with relatively less informed retail investors. Last, Barinov (2012) argues that turnover is a proxy for firm-specific uncertainty rather than liquidity. In sum, these findings are consistent with the notion that broadly defined liquidity measures might capture more of the adverse selection risks than the transaction costs of liquidity (Brennan and Subrahmanyam 1996, O'Hara 2003).

Third, we took into account potential industry effects and reestimated model (3) by excluding bonds issued by firms in financial or utility industries. The main rationale for such exclusion is that both financial and utility industries are heavily regulated. Also, in light of the recent financial crisis, a period that our sample overlaps, one may suspect that bonds of financial firms may have behaved differently. The

[25] To estimate the Amihud (2002) liquidity measure for each bond-quarter, we first calculate the price impact for each bond-day by dividing the absolute daily price changes by daily trade volume, whenever prices for two consecutive trading days are available. We then average the daily price impact over days within each quarter for each bond to obtain a bond-quarter-level estimate.

[26] The realized bid–ask spread is defined as the difference between average buying and selling prices per bond per day in Chakravarty and Sarkar (2003). We also used the intraday price volatility of a bond, a measure very similar to intraday price range, to control for liquidity and found similar results.

results, presented in panel C, show that the effects of information asymmetry on yield spreads are little changed. We also controlled for industry effects by including two dummy variables for financial and utility industries and estimated model (3) on the full sample of bonds, which yields similar results (not shown).

Fourth, we examined a more flexible specification of model (3) by replacing macroeconomic variables with year-quarter fixed effects. This specification allows us to control for some unobservable time-varying effects, such as the seasonal effects as documented in Campbell and Taksler (2003) or changes in risk appetite among average investors. As seen in panel D, the coefficients of information asymmetry measures remain largely unchanged.

Finally, because our information asymmetry measures are estimated with error, we took the inverse of the variance of the corresponding estimation errors for each bond-quarter as the weight to reestimate model (3) using a weighted least squares (WLS) approach. Once again, our results are robust to this alternative specification (panel E).

4.4. The Effects of Information Asymmetry by Credit Rating, Time to Maturity, and Public Equity Listing

In this section, we examine further whether the effects of information asymmetry on corporate yield spreads vary across bonds with different credit ratings and times to maturity. In addition, we explore the relationship between a firm's equity listing status and the effect of information asymmetry in bond trading on the costs of bond financing.

Our first goal here is to examine if there exist any nonlinear empirical regularities associated with credit risk. To do so, we followed the literature by separately examining the samples of investment- and speculative-grade bonds (e.g., Chen et al. 2007). The general rationale for this practice is that information asymmetry may exhibit a stronger pricing impact for lower rate bonds, because bonds are more sensitive to downside risks. Furthermore, investor behavior may differ when a bond is close to the default threshold, as opposed to when a bond has little default risk. In our context, investors may care more about the adverse selection risk in trading speculative-grade bonds as those bonds are closer to default.

We reestimated model (3) separately using the samples of high-yield and of investment-grade bonds. The results, presented in panel A of Table 7, show that the coefficients for information asymmetry measures are positive and statistically significant for both high-yield and investment-grade samples. Thus, the conditional effect of informed trading on bond spreads is not confined to high-yield bonds, even though, as we showed earlier, trading in high-yield bonds tends to have a higher degree of information asymmetry. The point estimate implies that a one-basis-point increase in the information asymmetry and the liquidity cost measures, respectively, leads to increases of 0.22 and 0.30 basis points in yield spreads for investment-grade bonds, and of 0.64 and 0.61 basis points for high-yield bonds. The liquidity cost effect is comparable to that documented by Chen et al. (2007), who find increases of 0.21 and 0.82 basis points in the yield spread for a one-basis-point increase in their estimated liquidity cost for investment-grade and high-yield bonds, respectively. Furthermore, the magnitudes of both information asymmetry and liquidity cost effects on the high-yield sample are stronger than those on the investment-grade sample, and the differences are statistically significant at the 1% level.

Theoretical work by Duffie and Lando (2001) indicates that incomplete accounting information can lead to a significant increase in yield spread for bonds with short times to maturity. Consistent with this prediction, Yu (2005) finds firms with lower accounting transparency tend to have larger yield spreads, especially for short-term bonds. Arora et al. (2011) find asset measurement uncertainty to be a significant determinant of short-term yield spreads. We also tried to shed some light on the impact of information asymmetry on the term structure of yield spreads by examining the differential pricing implications of information asymmetry for bonds of different maturities. For this purpose, we divided our sample bonds into two groups based on whether their time to maturity is less than or greater than five years, and reestimated model (3) separately on these two groups of bonds. As shown in panel B, information asymmetry affects yield spreads for both long- and short-term bonds, but such effect is much stronger for the short-term sample.

Our results on credit rating and term to maturity shed some light on the credit spread puzzle. For example, the point estimates based on the MRR model suggest that, when evaluated at the sample means, liquidity cost and information asymmetry components account for, respectively, 1.6% and 2.4% of the yield spreads for high-yield bonds and 2.9% and 1% for investment-grade bonds, and 5.1% and 2.2% for short-term bonds and 0.4% and 0.5% for long-term bonds. The results based on the GH model are similar. Therefore, by these point estimates, information asymmetry in bond trading helps explain the maturity aspects of the credit spread puzzle in that the pricing error of standard credit risk models is larger on the shorter end of maturity.

Last, we examined the effect of information asymmetry on the borrowing costs for private firms. For this purpose, we expanded our sample to include all bonds whose issuer has no publicly traded equity

Table 7 The Effects of Information Asymmetry by Credit Rating, Time to Maturity, and Public Equity Listing

	Panel A: By rating category				Panel B: By time to maturity				Panel C: Bonds issued by private firms	
	I. High-yield		II. Investment-grade		III. <5 years		IV. ≥ 5 years			
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
AsymInfo	0.635	0.000	0.215	0.000	0.582	< 0.0001	0.189	0.000	0.729	0.000
Liquidity	0.611	0.000	0.299	0.000	0.646	< 0.0001	0.080	0.000	0.498	0.000
Rating	0.579	0.000	0.126	0.000	0.896	< 0.0001	0.425	< 0.0001	2.546	0.000
Maturity	−0.079	0.000	−0.024	0.000	−0.076	< 0.0001	−0.027	< 0.0001	−0.070	0.000
Age	0.016	0.205	−0.018	0.000	−0.020	0.016	0.012	0.079	−0.050	0.000
IssueSize	−0.153	0.031	−0.053	0.007	−0.039	0.336	−0.267	< 0.0001	0.000	0.021
Coupon	0.573	0.000	0.232	0.000	0.115	< 0.0001	0.515	< 0.0001	0.271	0.000
OI/Sales	0.001	0.877	−0.072	0.000	−0.044	0.058	−0.001	0.806		
PretaxInterestCoverage	−0.002	0.422	−0.001	0.636	0.008	0.111	−0.002	0.144		
LTD/TA	−1.004	0.083	2.042	0.000	−0.057	0.890	0.057	0.862		
LD/TC	4.232	0.000	0.911	0.000	2.608	< 0.0001	0.495	0.180		
IssuerStockVolatility	97.478	0.000	50.475	0.000	72.713	< 0.0001	70.102	< 0.0001		
IssuerStockReturn	−20.865	0.036	5.889	0.150	−41.437	< 0.0001	−29.785	< 0.0001		
1yrTreasuryRate	−1.583	0.000	−0.139	0.000	−0.683	< 0.0001	−0.381	< 0.0001	−1.346	0.000
10yr− 2yrTreasuryRate	−2.128	0.000	−0.189	0.000	−0.881	< 0.0001	−0.585	< 0.0001	−1.708	0.000
EuroDollar	0.018	0.894	0.568	0.000	0.625	< 0.0001	0.426	< 0.0001	0.982	0.000
StockMarketReturn	−187.607	0.007	24.111	0.068	−74.623	0.012	−0.968	0.971	−255.141	0.000
StockMarketVolatility	86.137	0.000	19.110	0.000	1.956	0.768	43.604	< 0.0001	112.564	0.000
Adj. R^2	0.799		0.753		0.801		0.798		0.764	
N	4,262		10,898		6,719		8,441		12,384	
Firm fixed effect	Yes		Yes		Yes		Yes		Yes	

Notes. This table examines the influence of credit rating, time to maturity, and whether the issuer has a publicly traded stock on the effect of information asymmetry on corporate yield spreads. Panel A presents the results from estimating model (3) on the subsamples of high-yield and investment-grade bonds. In panel B, we classify bonds into either long-term or short-term bonds depending on whether their time to maturity is fewer or greater than five years, and estimate model (3) separately on these two groups of bonds. In panel C, we estimate model (3) on a sample of bonds whose issuer has no publicly traded stock during our sample period. *Information* and *Liquidity* refer to the information and liquidity cost measures estimated using the MRR model. Other explanatory variables include bond characteristics (such as credit rating (*Rating*), term to maturity (*Maturity*), number of years since issuance (*Age*), the log of the total amount of par at issuance (*IssueSize*), and coupon rate (*Coupon*)), firm characteristics (such as long-term debt/total assets (*LTD/TA*), total debt/total capitalization (*TD/TC*), operating income/sales (*OI/Sales*) and pretax interest coverage (*PretaxInterestCoverage*)), macroeconomic variables (the 1-year Treasury rate, the difference between 10-year and 2-year Treasury rates, and the difference between the 30-day Eurodollar and Treasury yields (*EuroDollar*)), the mean and standard deviation of the daily excess return of the issuer's equity (*IssuerStockReturn* and *IssuerStockVolatility*), and the mean and standard deviation of the daily stock market returns (*StockMarketReturn* and *StockMarketVolatility*) in each quarter. Adj. R^2 and N refer to the adjusted R^2 and sample size, respectively.

during our sample period. We find that compared with those issued by public firms, bonds issued by private firms have higher levels of information asymmetry. Based on the MRR model, the mean (median) value of the information asymmetry estimate for private firm bonds is 9.67 (5.15), significantly higher than that for public firm bonds, 6.97 (3.39). Both the t-test and the Wilcoxon test show that the difference is statistically significant at the 1% level. Similar results hold for the information asymmetry estimate based on the GH model.

We then reestimated model (3) for this sample of private firm bonds and the results are presented in panel C. We excluded firm-specific and equity-related variables because their values are missing for private firms. The coefficient for the information asymmetry measure is positive and highly significant. Noticeably, the magnitude of the coefficient is much higher than that from the public firm bond sample as reported in Table 3. Such stronger pricing effects of informed trading may reflect the fact that it is more costly to collect and analyze information on credit risks when the issuer is privately held. A caveat to this interpretation is that the estimated stronger information effect can also be attributed to some omitted variables for private firms. For instance, accounting information is generally not available for private firms. Also, public status can affect the costs of debt financing as access to public equity markets might render equity financing a more attractive choice, which may in turn decrease the issuer's leverage and credit risks. Nevertheless, our results highlight the importance of using bond market trading information to explain corporate yield spreads when the issuer has no publicly traded equity.

5. Information Asymmetry and Corporate Default Prediction

We now examine whether microstructure measures of information asymmetry help predict corporate

Table 8 Information Asymmetry and Corporate Default Prediction

	Public firms						Private firms					
	I		II		III		IV		V		VI	
					Panel A: Using MRR asymmetric information measure							
Intercept	−5.615	< 0.0001	−3.435	< 0.0001	0.001	0.871	−5.240	< 0.0001	−5.032	< 0.0001	0.136	0.367
AsymInfo	1.369	0.001	0.862	0.050	0.080	0.089	1.611	< 0.0001	1.288	0.000	0.378	0.003
DtoD			−0.461	< 0.0001	−0.001	< 0.0001						
StockRet			−0.938	< 0.0001	−0.018	< 0.0001						
Tbill			−0.106	0.455	0.001	0.422			0.027	0.788	0.005	0.874
SPX			−0.428	0.824	0.030	0.091			−3.525	0.007	−1.001	0.109
Pseudo-R^2	0.020		0.286		0.233		0.028		0.042		0.027	
N	8,173		8,173		7,493		9,084		9,084		6,245	
					Panel B: Using GH asymmetry information measure							
Intercept	−5.601	< 0.0001	−3.434	< 0.0001	0.001	0.944	−5.277	< 0.0001	−5.087	< 0.0001	0.138	0.423
AsymInfo	1.479	0.001	0.995	0.044	0.099	0.089	1.955	< 0.0001	1.644	< 0.0001	0.423	0.002
DtoD			−0.460	< 0.0001	−0.001	0.000						
StockRet			−0.942	< 0.0001	−0.018	< 0.0001						
Tbill			−0.106	0.456	0.001	0.411			0.029	0.772	0.005	0.875
SPX			−0.453	0.814	0.031	0.090			−3.439	0.008	−0.998	0.134
Pseudo-R^2	0.020		0.289		0.232		0.035		0.049		0.027	
N	8,173		8,173		7,493		9,084		9,084		6,245	

Notes. This table examines whether information asymmetry in corporate bond trade can help predict corporate defaults. We estimate model (4) with information measures (*AsymInfo*) from both the GH and MRR models, and the results are presented in panels A and B, respectively. In each panel, model (4) is estimated both with and without default forecasting variables from Duffie et al. (2007): the issuer's distance to default measure (*DtoD*), the issuer's trailing one-year stock return (*StockRet*), the three-month Treasury bill rate (*Tbill*), and the trailing one-year return on the S&P 500 index (*SPX*). We also use the same instrument variable developed in §4 to control for potential endogeneity between information asymmetry and credit risks in the prediction of defaults. Results from estimating the second stage of the 2SLS regressions are presented in columns III and VI. We examine the power of information asymmetry in bond trading in predicting defaults separately for public and private firms.

defaults. As discussed in the introduction, one possible channel of such predictability lies in the premise that bonds are more information sensitive when the issue is closer to default. Because informed trading increases when the firm's credit quality deteriorates, the adverse selection risk in bond trading rises and results in greater bond illiquidity, which may make it more costly or difficult for the issuer to refinance existing debt and in turn raise its default risk.

We obtained data on the timing of bond defaults from Moody's Default Risk Service, supplemented using information on defaults in the Mergent's FISD database, for the period of 2003 to 2008. Defaults are defined as bankruptcy filings, missing coupon or principal payments, and distressed exchanges (when a firm issues new securities in the form of lower economic values, such as reduced principal amount or lower coupon, to exchange for its existing debt). For the sample period, we were able to identify a total of 98 defaulted firms, 61 public and 37 private, for which we had nonmissing estimated measures of information asymmetry in bond trading during the quarter prior to their defaults. For each firm-quarter with information asymmetry measures, we created a dummy variable, *Defaultdum*, which takes the value 1 if the issuer defaults on its bonds during the next quarter, and 0 otherwise. We estimated a logistic regression of default dummy on the same set of forecasting variables as used by Duffie et al. (2007): the issuer's distance to default measure (*DtoD*), the issuer's trailing one-year stock return (*StockRet*), the three-month Treasury bill rate (*Tbill*), and the trailing one-year return on the S&P 500 index (*SPX*); that is, the latent dependent variable of the logistic regression is

$$y_{i,t} = \gamma_0 + \gamma_1 AsymInfo_{i,t} + \gamma_2 DtoD_{i,t} + \gamma_3 StockRet_{i,t} + \gamma_4 Tbill_{i,t} + \gamma_5 SPX_{i,t} + \varepsilon_{i,t}, \tag{4}$$

such that $Defaultdum = 1$ if $y_{it} > 0$ and 0 otherwise. We presented the model estimations in Table 8, with panels A and B using MRR and GH information asymmetry measures, respectively.

The results for public firms are shown in columns I and II. We first considered a special case of the specification of model (4), where the *AsymInfo* measure is the only explanatory variable. As shown in column I, the degree of informed trading carries significant power in forecasting corporate defaults, because the coefficient for the *AsymInfo* measure is positive and statistically significant at the 1% level. In our full specification of model (4), with other default forecasting variables, column II, the *AsymInfo* measure continues to contribute to forecasting defaults: the *AsymInfo* measure remains statistically significant at the 5% level, and the resulting pseudo-R^2 is 29%, about 8% higher than the pseudo-R^2 of the same logit regression with all explanatory variables other than *AsynInfo* (not shown).[27] The estimates of the coefficients for the other four predictive variables are largely consistent with Duffie et al. (2007). The coefficients for both *DtoD* and *StockRet* are negative and highly significant, suggesting that firms with lower leverage (after adjusting for volatility) and higher stock returns tend to have lower probability of default in the next quarter. The coefficients for both the Treasury bill rate and the S&P 500 index return are also negative, but not statistically significant at any conventional levels.

In addition, we use the same instrument variable developed in §4 to control for potential endogeneity between information asymmetry and credit risks in the prediction of defaults. In the first stage, information asymmetry measures are regressed on the *Herf* variable and all other control variables used in model (4). In the second stage, we reestimate model (4) by replacing the original estimates of information asymmetry measures with their predicted values from the first stage regressions. As shown in column III, the magnitude of the coefficient of *AsynInfo* drops, but the estimate remains positive and significant at the 10% level.

In columns IV, V, and VI, we show the power of informed bond trading in predicting defaults for private firms. We find that the coefficient for the *AsymInfo* measure is positive and significant at the 1% level in the univariate logit specifications (column IV). This result holds even after we controlled for the other two default predictive variables, *Tbill* and *SPX* (column V), and potential endogeneity between information asymmetry and credit risks (column VI). Note that the significance of the coefficient of the *AsymInfo* measure, as well as pseudo-R^2, is higher here than that for the public firm sample, consistent with our expectation that trading in bonds of private firms tends to be more informative about future defaults than that for their public counterparts (see columns I and IV). Certainly, these results may also be attributed to the fact that, for private firms, we are unable to compute two default predictive variables related to the issuer's equity information. Nonetheless, this result highlights the potential importance of using bond trading information in default prediction for these firms.

6. Conclusion

Valuation of corporate debt has been an important, albeit imprecise, task in asset pricing. Both structural and reduced-form models have had limited success in explaining observed corporate yield spreads. Taking advantage of a unique corporate bond transaction data set, we introduce the effect of information asymmetry into corporate bond pricing. We find that microstructure measures of information asymmetry seem to capture adverse selection in corporate bond trading reasonably well. We demonstrate that information asymmetry exhibits additional explanatory power for corporate yield spreads after controlling for liquidity costs, credit risks, and other relevant factors in bond pricing. The effects of information asymmetry on yield spreads are stronger for lower rated and shorter term bonds, and for bonds issued by privately held firms. This paper extends the literature on the implications of market microstructure for asset pricing to corporate debt securities and suggests that yields of corporate debt might embed an information premium that is largely unexamined in existing corporate bond pricing models. Therefore, valuation of corporate debt needs to be recast in broader terms to integrate transaction costs of liquidity and risks from information asymmetry during the process of price discovery.

In addition, this paper highlights the value of information embedded in bond trading in forecasting the issuer's future defaults. We find that the degree of informed trading in corporate bonds helps predict the issuer's future defaults after conditioning on other default forecasting variables. Such predictive power is stronger for private firms with no firm-level accounting information and publicly traded stocks.

Furthermore, this paper suggests that the information structure surrounding a firm's debt has important effects on its financing and risk management decisions. If there is significant information-based trading in a firm's 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 disclosure policies, market microstructure, accounting treatments, and other factors that will influence the information structure surrounding its debt securities. It provides a new perspective to understanding the complete market assumption in the Modigliani and Miller (1963) theorem.

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[27] The pseudo-R^2 of the logit regression of default with all explanatory variables other than *AsynInfo* is 26%, a level similar to what has been found in existing studies with such specifications. See, for example, a recent study by Campbell et al. (2011).

Toronto, the American Economic Association Annual Meetings, and the Conference on Capital Markets and Corporate Finance at the Shanghai University of Finance and Economics.

Appendix

Estimating Default-Free Zero-Coupon Interest Rates by Using the Extended 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:

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

$$\text{subject to} \quad r(m_{\min}) \geq 0,$$

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

and

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

where

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

and

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

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

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