

## Accrual quality, bond liquidity, and cost of debt

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## **Accrual quality, bond liquidity and cost of debt**

### **Abstract**

This paper investigates the effect of accrual quality on bond liquidity and the implications of this effect for cost of debt. We argue that high accrual quality not only reduces information asymmetry but also decreases uncertainty, thereby improving liquidity, which in turn lowers the cost of debt. We first document that higher accrual quality is associated with higher bond liquidity. We then show that accrual quality reduces cost of debt but this effect is subsumed by liquidity, suggesting that the effect of accrual quality on reducing cost of debt arises largely through its effect on improving bond liquidity. Further analyses reveal that our primary results are robust to controlling for information asymmetry (through PIN), suggesting that our documented effect arises through aspects of liquidity that are independent of information asymmetry. We also show that credit ratings reflect the underlying structural relations among accrual quality, bond liquidity and cost of debt, albeit in an incomplete manner.

**Keywords:** bonds; liquidity; cost-of-debt; accrual quality

## Accrual quality, bond liquidity and cost of debt

### 1. Introduction

During the recent financial crisis, poor information quality created uncertainty about the value of mortgage securities, dried up liquidity and crashed security prices in the debt markets. This triggered a financial contagion that spread to other markets, plunging economies into a severe slump that they are still struggling to overcome (Krishnamurthy, 2009). The events that led to the financial crisis underscore the following. First, debt markets are of vital importance to the economy. Second, liquidity is crucial to the orderly functioning of the debt markets. Third, information quality is crucial to maintaining liquidity. For these reasons, it is important to study the effect of information quality on debt market liquidity and the implications of this effect on the pricing of debt securities.

The extant literature, however, has focused primarily on the effect of accrual quality on cost of *equity*, from the angle of whether “information risk” is a non-diversifiable factor that is priced by the stock market (e.g., Francis et al., 2004; Core et al., 2008; Hughes et al., 2007). Despite its importance, the effect of accrual quality on *debt* markets’ *liquidity* and its implications for the pricing of *debt* securities is yet to be examined. In this paper, we attempt to fill this void. Specifically, we investigate (1) the effect of accrual quality on bond liquidity; and (2) the implications of this effect for the effect of accrual quality on the cost of debt—in particular, whether the documented negative relation between accrual quality and cost of debt (Francis et al., 2005) is explained by the effect of accrual quality on bond liquidity.

We begin by hypothesizing that accrual quality improves bond liquidity for two reasons. First, high quality information reduces *information asymmetry*, which improves liquidity by reducing bid-ask spreads and increasing depth (Kyle, 1985). Second, high quality information

improves liquidity by reducing *uncertainty* about asset values and facilitating trading between better informed buyers and sellers (Easley and O'Hara, 2010). In addition, in the bond market, lowered uncertainty reduces the market maker's inventory and search costs, which also results in improved liquidity (Amihud and Mendelson, 1980).

Next, we extend this hypothesized relation between accrual quality and bond liquidity to explain the effect of accrual quality on cost of debt. Prior literature documents that liquidity lowers expected returns (e.g., Amihud and Mendelson, 1986) and, in particular, that higher liquidity is associated with lower cost of debt (Chen et al., 2007). Therefore, we hypothesize that, if accrual quality improves bond liquidity, it can lower cost of debt *indirectly* through its effect on liquidity. In contrast, prior literature has argued that accrual quality lowers cost of capital, both equity and debt, by reducing information risk that is priced by the capital markets through reduced information asymmetry (Easley et al., 2002, 2004; Francis et al., 2005; Bhattacharya et al., 2009).

Liquidity measures such as bid-ask spreads or its components like PIN, are often used as proxies for information asymmetry (Easley et al., 2002; Bhattacharya et al., 2009). In this paper, however, we examine liquidity as a distinct economic construct rather than as a proxy for information asymmetry. Examining liquidity in this manner has advantages. First, liquidity has a broader connotation than information asymmetry and can be affected by other information characteristics such as uncertainty (Easley and O'Hara, 2010). Second, while it is still debatable that information asymmetry is priced (Mohanram and Rajgopal, 2009; Duarte and Young, 2009), it is less controversial that liquidity is priced by the capital markets (Amihud et al., 2005; Chen et al., 2007).

We test our predictions on a sample of 1,310 firm-year observations from 1995 to 2007. Following Chen et al. (2007), we measure bond liquidity alternatively using percentage of non-zero returns and bid-ask spreads.<sup>1</sup> We measure cost of debt using yield spreads, which is the yield-to-maturity on a corporate bond minus the yield-to-maturity on a maturity matched Treasury bond. Consistent with prior research, our first measure of accrual quality is the modified Dechow and Dichev (1999) measure proposed by Francis et al. (2005) (hereafter, *FLOS*). To alleviate the concern that *FLOS* largely captures the effects of operating volatility (Liu and Wysocki, 2007), we also use an adjusted *FLOS* measure (hereafter, *ADJFLOS*) that is orthogonal to operating accruals' volatility.

We begin our analysis by separately regressing the two bond liquidity measures on the two accrual quality measures. In all regressions, we control for bond characteristics such as age, maturity, and offering amount, and firm characteristics such as size, profitability, leverage, book-to-market, operating volatility and analysts following. We find a positive and significant coefficient on accrual quality in each of our four regressions. This effect is economically significant. For example, moving from the 5<sup>th</sup> to the 95<sup>th</sup> percentile of accrual quality results in an average increase of 10 to 15 percent in non-zero trading days and a 0.07% to 0.10% reduction in bid ask spreads.

We next examine whether the effect of accrual quality on cost of debt can be explained by the effect of accrual quality on bond liquidity. After controlling for both bond and firm characteristics, we find a negative association between the cost of debt and accrual quality,

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<sup>1</sup> We conduct all our tests on a firm-year basis. For all bond-related variables, such as liquidity measures, yield spreads, and bond characteristics, we use weighted average firm-year measures, where the weights are proportional to the outstanding principal amounts of each bond.

consistent with prior findings (e.g. Francis et al., 2005).<sup>2</sup> When liquidity proxies are included in the regression, however, the statistically significant association between accrual quality and cost of debt disappears. Moreover, the decrease in the magnitude of the coefficient on accrual-quality after the inclusion of liquidity is both statistically and economically significant (a reduction of 52% in both the *FLOS* and *ADJFLOS* coefficients). Overall, our results suggest that the association between accrual quality and cost of debt arises to a large extent through the association between accrual quality and bond liquidity.

We study liquidity as a distinct economic construct rather than as a proxy for information asymmetry and argue that accrual quality may affect components of liquidity unrelated to information asymmetry. To ensure that our results are not driven by the information asymmetry component of liquidity, we replicate all our primary analyses after controlling for a well-accepted proxy for information asymmetry, the probability of informed trading (PIN). We find that the inclusion of PIN in the regressions does not affect any of our results—in fact, none of the coefficients on accrual quality change significantly after controlling for PIN. Our primary inferences (i.e., that accrual quality is positively associated with liquidity and that accrual quality is negatively related to cost of debt, but this association decreases significantly and becomes insignificant after controlling for liquidity) remain unchanged. These findings alleviate the concern that our primary results are driven by the information asymmetry component of liquidity, thereby differentiating our liquidity explanation from the information asymmetry explanation suggested earlier (Francis et al., 2005; Bhattacharya et al., 2009).

Finally, we address the role of credit ratings in our analysis. Most cost of debt papers include credit ratings in their regressions as an all-encompassing control for credit risk (for

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<sup>2</sup> This effect is also economically significant. For example, moving from the 5<sup>th</sup> to the 95<sup>th</sup> percentile of accrual quality results in an average decrease of 0.21% (*ADJFLOS*) to 0.32% (*FLOS*) in yield spread.

example, Chen et al., 2007; Jiang, 2008). We do not control for credit ratings in our primary analysis because we are interested in studying the underlying structural relations among accounting quality, liquidity and cost of debt independent of whether the credit rating agencies reflect this information in their ratings or not. Nevertheless, in separate analysis we study the complex relations between credit ratings on the one hand and accounting quality, liquidity and cost of debt on the other. We first examine whether ratings incorporate the triangular relation between bond liquidity, accrual quality, and cost of debt. We find that they do—accrual quality is associated with better credit ratings and the extent of this association decreases significantly after controlling for liquidity. Next, we examine whether controlling for credit ratings subsume the underlying structural relations among accounting quality, liquidity and cost of debt and find that it does not do so qualitatively. Overall, this evidence suggests that credit raters do understand the triangular relation between accounting quality, liquidity and cost of debt, but they do not completely incorporate this information in their ratings.

Our study contributes to the literature in several ways. First, to the best of our knowledge, this paper is the first to investigate the role of accrual quality in improving bond liquidity. Recent working papers (Bhattacharya et al., 2009; Ng, 2009) examine the association between accrual quality and liquidity (or liquidity risk) in the stock market. It is important to understand the role of accrual quality in the bond market because corporate bonds are a primary source of external financing and bond liquidity plays a vital role in the economy. In addition, the microstructure of the bond market makes liquidity more important for bonds than for stocks, therefore providing a more powerful setting to detect the effect of accrual quality on liquidity. Second, unlike much of the prior literature where liquidity is merely used as a surrogate for information asymmetry when examining the effect of accrual quality (e.g., Easley et al., 2002, 2004; Bhattacharya et al., 2009),

we study liquidity as a distinct economic construct. The recent financial crisis suggests that uncertainty, or the general level of informedness of traders, plays a crucial role in determining liquidity in the debt markets (Easley and O’Hara, 2010). Therefore, it is important to examine the effect of accrual (information) quality on liquidity in general, rather than simply its asymmetric information component. Third, we provide insights into how accrual quality affects the cost of debt through its effect on bond liquidity. We show that the effect of accrual quality on cost of debt arises largely through its effect on bond liquidity and in particular, the part of liquidity that is independent of information asymmetry.

An important caveat is that we examine the effect of one type of information quality—accrual quality—on the liquidity of one type of debt security—corporate bonds. We acknowledge that our analysis does not directly address issues that triggered the recent financial crisis, i.e., uncertainty about valuation of mortgage securities that destroyed liquidity in the subprime mortgage market—neither the type of security we study, i.e., corporate bonds, nor the type of information quality we examine, i.e., accrual quality, was directly implicated in the financial crisis. Our motivation for invoking the financial crisis is merely to highlight the importance of debt market liquidity to the economy and the role of information quality in maintaining liquidity in the debt markets. The contribution of our paper, however, is limited to studying the effects of accrual quality on corporate bond liquidity.

## **2. Motivation**

### *2.1 The importance of studying information quality and liquidity in the debt market*

The U.S. corporate bond market is enormous. For example, in 2008 the principal value of outstanding corporate bonds was \$6.2 trillion. In addition, bonds are one of the primary sources of external financing for U.S. corporations and are bigger than equity financing. For example,



during the ten-year period 1999-2008, U.S. corporate bond issues amounted to \$17.2 trillion, compared to only \$1.9 trillion of equity issuance.<sup>3</sup> Thus the importance of the corporate bond market for the business sector and even the entire economy cannot be overemphasized.

Liquidity is vital to well-functioning debt markets. For example, during the recent financial crisis, illiquidity originated in the subprime mortgage market and spread rapidly to other debt markets, creating a financial contagion that crashed asset prices and a flight from risky assets. The resulting credit crunch led to an economic slump that the U.S. and other economies are still struggling to overcome. In fact, several authors have argued that the recent financial crisis was the product of the liquidity crisis in the debt markets (Getter et al., 2007; Krishnamurthy, 2009).

A key factor implicated in precipitating this liquidity crisis is poor information quality, i.e., uncertainty about asset values (Easley and O'Hara, 2010; Getter et al., 2007). For example, Krishnamurthy (2009) concludes that when faced with uncertainty, investors disengage from risks and seek liquid investments, which can lead to a liquidity crisis dynamic. Similarly, Easley and O'Hara (2010) model illiquidity during the financial crisis as arising from uncertainty or poor information quality about asset values. These viewpoints are broadly consistent with earlier literature relating information quality to illiquidity and market failure (e.g., Akerlof, 1970) and underscore the crucial role that information quality plays in maintaining liquidity in the debt markets.

In summary, information quality is important for maintaining liquidity in the debt markets, which in turn is important for well-functioning debt markets and even the economy as a whole. Despite the importance of this topic, we are unaware of academic research investigating the association between information quality and debt market liquidity. In this paper, we fill this

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<sup>3</sup> Source: Securities Industry and Financial Markets Association ([www.sifma.org](http://www.sifma.org))

void by examining whether higher accrual quality is associated with higher bond liquidity and whether this association explains the relation between accrual quality and cost of debt.

## *2.2 The relation between accrual quality and bond liquidity*

Theory suggests that information asymmetry contributes to illiquidity. In his seminal work, Akerlof (1970) shows how information asymmetry about product quality in the presence of adverse selection can lead to a vicious cycle where liquidity dries up and the market completely shuts down. Under more normal circumstances, in specialist markets such as the bond market, specialists (i.e., market makers) cannot distinguish between informed traders who have private information and uninformed traders who trade for non-informational reasons. To price protect themselves in the presence of information asymmetry, market makers charge a premium by increasing bid-ask spreads or decreasing depth (Kyle, 1985; Glosten and Milgrom, 1985), thereby decreasing liquidity. The issue of information asymmetry is of particular importance to the bond market because (1) bonds are mostly held by institutional investors who are generally more informed than retail investors who proliferate the stock market; and (2) the opaqueness of the over-the-counter bond market makes it harder for specialists to glean private information from order flow.<sup>4</sup>

Diamond and Verrecchia (1991) suggest that public information can increase liquidity by reducing information asymmetry and thus prevent the type of market failure predicted by Akerlof. Similarly in specialist markets such as the bond market, high quality public information reduces information asymmetry by lowering the value of the private information held by informed traders, which in turn lowers the price-protection demanded by the specialists and improves liquidity (e.g., Kyle, 1985). Consistent with these theoretical predictions, we

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<sup>4</sup> Even though the introduction of the Transaction Reporting and Compliance Engine (TRACE) in July 2002 has improved the transparency of the bond market, it still does not make the corporate bond market as transparent as the stock market (Bessembinder and Maxwell, 2008).

hypothesize that high accrual quality improves liquidity in the bond market by reducing information asymmetry.

In addition to information asymmetry, i.e., the *relative differences* in the informedness across traders, uncertainty, i.e., the *overall level* of informedness of traders, can also affect liquidity. Theoretically, this occurs because information quality affects how aggressively traders trade (e.g., Holthausen and Verrecchia, 1990). In the recent financial crisis it was the absence of information about the value of mortgage securities (i.e., uncertainty) rather than any informational disadvantage across different classes of traders (i.e., information asymmetry) that precipitated the liquidity crisis (Easley and O'Hara, 2010; Krishnamurthy, 2009).<sup>5</sup> Intuitively, when traders are uncertain (i.e., less informed) about a security's value they cannot agree on a price and are therefore less willing to trade, thereby reducing liquidity.

In addition to this effect, in specialist markets such as the bond market, uncertainty can further decrease liquidity through increased inventory and search costs. Specialists (market makers) bear inventory costs because holding securities on their account exposes them to future price changes, that is, inventory risk (Amihud and Mendelson, 1980). Less informed specialists are subject to inventory risk from price changes and therefore their inventory costs are higher. Also, in the bond markets, which are typically less liquid and more dominated by large traders than the stock market, specialists incur search costs to locate counterparties and induce them to trade through price discounts. It is more difficult to locate counterparties when traders are poorly informed because traders are less willing to trade when faced with uncertainty. Therefore, poor information quality increases search frictions and makes it difficult for specialists to more easily

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<sup>5</sup> Reiterating this point, Peter Orszag, the director of the Congressional Budget Office, noted that "...one reason that credit markets have seized up is the uncertainty about who holds impaired assets and what they are worth, especially those related to mortgages". The popular press holds the same view. As commented by a reporter, "unbounded uncertainty is deadly to market psychology. It creates a 'head for the exits' mentality."  
[http://www.homerdixon.com/download/unbounded\\_uncertainty.pdf](http://www.homerdixon.com/download/unbounded_uncertainty.pdf)

adjust order imbalances without changing prices. Because there is no centralized bond market and bond investors trade bilaterally, both inventory cost and search costs are higher for bond-market specialists than for stock exchanges. To summarize, uncertainty increases both inventory and search costs incurred by specialists, who in turn increase bid-ask spreads and decrease depths, thereby reducing liquidity. Consistent with these arguments, we hypothesize that accrual quality improves liquidity in the bond markets by also reducing uncertainty.

Two concurrent working papers examine the association between accrual quality and liquidity in the stock market. Bhattacharya et al. (2009) argue that high earnings quality reduces information asymmetry and therefore improves liquidity. They find that higher earnings quality is associated with lower information asymmetry component of the bid-ask spread for stocks. Ng (2009) investigates the effect of information quality on liquidity risk instead of liquidity cost. Specifically, Ng hypothesizes that the returns of a stock with high information quality are less sensitive to changes in market liquidity. He finds that high information quality reduces liquidity risk and this effect helps explain the relation between information quality and cost of equity.

In contrast to these papers that examine the effect of accrual quality on liquidity in the stock market, we study how accrual quality affects liquidity in the bond market. Our study is important for the following reasons. First, as noted earlier, the bond market is arguably no less important than the stock market to the economy. Second, as the recent financial crisis highlights, liquidity in the debt markets is of vital importance to the economy. While there is a large literature related to stock market liquidity, researchers have only recently started examining issues related to bond liquidity (e.g., Chen et al., 2007). Third, as discussed earlier, the bond market has several unique features—such as higher information asymmetry and higher inventory and search costs—that make liquidity more important for bonds than for stocks. Fourth, partly

because of its unique features, illiquidity is a more widespread phenomenon in the bond market. In contrast, stocks other than for the tiniest companies are fairly liquid.<sup>6</sup> Figure 1 illustrates this point by examining the mean percentage of non-trading days (zero returns) by firm size for a large cross-section of stocks and bonds. Two issues are worth noting. First, the number of non-trading days for bonds is significantly higher than those of stocks, irrespective of firm size. This suggests that the bond market is substantially more illiquid than the stock market in general. Second, except for the very small firms, stocks appear to be traded on all days. This is not true with bonds—bonds of even large firms have a large proportion of non-traded days. Overall, the evidence in Figure 1 suggests that illiquidity is a more widespread phenomenon for bonds than for stocks. For all these reasons, we argue that the bond market is a more powerful setting to study the effect of information quality on liquidity.

### *2.3 Earnings quality, bond liquidity, and the cost of debt*

A burgeoning literature on information risk provides theoretical and empirical support for the notion that information quality is priced into a firm's cost of capital (e.g., Easley and O'Hara, 2004; Francis et al., 2005). Theoretically, this literature suggests that information quality is priced in a firm's cost of capital through reduced information asymmetry.<sup>7</sup> Earlier papers such as Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) theorize an indirect link between information asymmetry (arising from poor public information quality) and the cost of capital through the information asymmetry component of the firm's bid-ask spreads. More recently papers such as Easley and O'Hara (2004) propose a model wherein information asymmetry arising from poor information quality is a non-diversifiable risk that is directly

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<sup>6</sup> Nallareddy and Subramanyam (2010) show that most of the variation in stock liquidity occurs for the tiniest ("micro") stocks—liquidity has a limited role for stocks that constitute more than 97% of the market capitalization.

<sup>7</sup> Lambert et al. (2007) model a direct effect of information quality on cost of equity capital through its effect on the conditional covariance of a firm's cash flows with that of the market. The Lambert et al. theory is less relevant to our study, which focuses on the indirect effect of information quality on cost of debt through liquidity.

reflected in the firm's expected return. Consistent with this argument, Easley et al. (2002) find that PIN (a proxy for information asymmetry) is associated with realized returns. Also, Francis et al. (2005) finds empirical support for poor accrual quality being associated with high implied cost of equity.

The link between information quality and cost of capital, however, has been disputed on both theoretical and empirical grounds. Theoretically, the non-diversifiability of information risk has been questioned. For example, Hughes et al. (2005) conclude that information risk is either diversifiable or subsumed by existing risk factors. Also, Lambert et al. (2007) find that when the number of traders becomes sufficiently large, information risk is fully diversifiable. Empirically, Core et al. (2008) dispute the findings of Francis et al. (2005) by showing that that accrual quality is not a priced risk factor in the stock market, that is, it has no association with future stock returns. Also, Mohanram and Rajgopal (2009) cast doubts on whether the information asymmetry (proxied by PIN) reflects information risk that is systematically priced by equity investors. Furthermore, Duarte and Young (2009) report that the PIN component related to asymmetric information is not priced in the stock market, while the PIN component related to illiquidity is priced.

In this paper, we explore an alternative path through which accrual quality could affect the cost of capital: indirectly through its effect on liquidity. Theory and empirical evidence suggests that liquidity has a statistically and economically significant effect on asset prices (Amihud et al., 2005). For example, a large body of research finds that illiquidity increases expected stock returns (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996) and yield spreads on corporate bonds (Chen et al., 2007). Since liquidity is well accepted as a priced risk

factor, we hypothesize that accrual quality affects the cost of capital indirectly through its effect on liquidity.

We acknowledge this liquidity path has been explored earlier in the context of information asymmetry, both theoretically (e.g., Diamond and Verrecchia, 1991; Kim and Verrecchia, 1994) and empirically (Bhattacharya, et al., 2009). Unlike the earlier literature, however, we study liquidity as a distinct economic construct and not merely as an embodiment of information asymmetry. This is important because, as noted earlier, liquidity has components that are unrelated to information asymmetry (such as inventory cost and search cost) and information characteristics unrelated to information asymmetry (such as uncertainty) can affect liquidity, especially in the bond market. Also, whether information risk arising from information asymmetry is priced is still controversial. To differentiate our liquidity path from the information asymmetry path, we empirically test whether the liquidity path exists after controlling for information asymmetry.

An important related paper is by Ng (2009), who examines whether liquidity risk subsumes much of the cost-of-capital effects of information quality in the stock market. Our focus, however, is the bond market. In addition, we study liquidity itself as opposed to liquidity risk, which Ng defines as the co-movement of stock returns with market liquidity (Pastor and Stambaugh, 2003).

In summary, we propose that accrual quality reduces cost of debt by improving liquidity. Because both accrual quality (Francis et al., 2005; Bharath et al., 2008) and bond liquidity (Chen et al., 2007) have independently been shown to reduce cost of debt, there is a triangular relation among accrual quality, bond liquidity, and cost of debt. We test this triangular relation by

examining whether liquidity is a possible channel through which accrual quality affects the cost of debt.

### **3. Sample, variables, and descriptive data**

#### *3.1. Sample selection*

We start from the Thomson Reuters Datastream database and collect daily price and yield spread data for 2,125 firms from 1994 to 2009. We merge the Datastream data with the Mergent Fixed Income Securities Database (FISD) to obtain bond characteristics such as issuing amount, maturity, and credit rating. This step excludes 52 firms. We next merge this data with Compustat to collect financial data and obtain 1,104 firms with necessary data.

We manually collect quarterly bid and ask prices from the Bloomberg Terminal, which are available for 499 of the 1,104 firms. The loss of observations from merging with Bloomberg is significant but not unusual.<sup>8</sup> We eliminate observations with negative spreads, negative total assets, negative book or market value of equity. We also exclude utility firms and financial firms. After requiring data on accrual quality measures and control variables, we obtain our final sample of 1,310 firm-years representing 251 distinct firms from 1995 to 2007.<sup>9</sup> We note that the actual numbers of observations in our regression models are slightly lower than 1,310 because of the application of outlier control techniques. Specifically, in all regressions, we delete observations with absolute studentized residuals greater than two (Belsley et al., 1980). Also, the additional analysis that involves PIN is based on a reduced sample of 1,182 firm-years (246

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<sup>8</sup> For example, Chen et al. (2007) report that they collect bid and ask prices from Bloomberg for 4,486 bond-years from 1995 to 2003, and our sample has 5,002 bond-years for the same time period. Nevertheless, we examine whether our Bloomberg sample is biased in any significant dimension compared to the initial Datastream/FISD/Compustat sample. Untabulated results indicate that our Bloomberg sample has much larger market values and total assets. However, we do not find any other significant differences in firm characteristics across the two samples.

<sup>9</sup> Our sample period changes from 1994-2009 to 1995-2007 because we require 20 observations for each industry year with non-missing input variables to estimate accrual quality and our accrual quality measures require both lagged and forward-looking information.



firms) due to the missing PIN measure.

### 3.2. Proxies and variable definitions

#### 3.2.1. Accrual quality measures

Table 1 provides the definition of all variables used in the analyses. We use two alternative accrual quality measures based on Francis et al. (2005). The first accrual quality measure, *FLOS*, is proposed by Francis et al. (2005) and estimated by combining the Dechow and Dichev (1999) and Jones (1991) models. Specifically, we estimate the following regression separately for each of Fama and French's (1997) 48 industry group and year:<sup>10</sup>

$$\frac{TCA_{j,t}}{Assets_{j,t}} = \alpha_{0,j} + \alpha_{1,j} \frac{CFO_{j,t-1}}{Assets_{j,t}} + \alpha_{2,j} \frac{CFO_{j,t}}{Assets_{j,t}} + \alpha_{3,j} \frac{CFO_{j,t+1}}{Assets_{j,t}} + \alpha_{4,j} \frac{\Delta Rev_{j,t}}{Assets_{j,t}} + \alpha_{5,j} \frac{PPE_{j,t}}{Assets_{j,t}} + v_{j,t}$$

where  $TCA_{j,t}$  is firm  $j$ 's total current accrual, computed as  $\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ ,  $Assets_{j,t}$  is firm  $j$ 's average total assets in year  $t$ ,  $CFO_{j,t}$  is firm  $j$ 's cash flow from operations in year  $t$ , computed as  $NI_{j,t} - TA_{j,t}$ , where  $NI_{j,t}$  is firm  $j$ 's net income before extraordinary items (IB in Compustat),  $TA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - Depre_{j,t}$ .  $\Delta CA_{j,t}$  is firm  $j$ 's change in current assets (ACT in Compustat),  $\Delta CL_{j,t}$  is firm  $j$ 's change in current liabilities (LCT in Compustat),  $\Delta Cash_{j,t}$  is firm  $j$ 's change in cash (CHE in Compustat),  $\Delta STDEBT_{j,t}$  is firm  $j$ 's change in debt in current liabilities (DLC in Compustat), and  $Depre_{j,t}$  is firm  $j$ 's depreciation and amortization expenses (DP in Compustat),  $\Delta Rev_{j,t}$  is firm  $j$ 's change in revenues (SALE in Compustat), and  $PPE_{j,t}$  is firm  $j$ 's gross value of property, plant, and equipment (PPEGT in compustat). After estimating this regression for each industry-year combination, we compute the rolling standard deviation of each firm-year's residuals from this regression over the prior ten-year period (i.e., over year  $t-9$  through  $t$ ).<sup>11</sup> Since large standard deviations indicate poor accrual

<sup>10</sup> Consistent with Francis et al. (2005), we exclude industries with less than twenty firms in a year.

<sup>11</sup> As a robustness check, we also use an alternative seven-year estimation window ( $t-6, t$ ) and the results are similar.

quality, we multiply the standard deviation by -1 so that higher values of this measure represent better accrual quality. This gives us the first accrual quality measure, *FLOS*.

To alleviate the concern that *FLOS* captures operating volatility manifested in accruals (Liu and Wysocki, 2007), we also estimate a second accrual quality measure (*ADJFLOS*) as the residual from the following pooled regression:

$$FLOS_{j,t} = \alpha_0 + \alpha_1 \times SDACCR_{j,t} + v_{j,t}$$

where  $FLOS_{j,t}$  is firm  $j$ 's *FLOS* measure in year  $t$ , and  $SDACCR_{j,t}$  is the rolling standard deviation of firm  $j$ 's current accruals over years  $t-9$  through  $t$ .<sup>12</sup>

### 3.2.2. Bond liquidity measures

We use two alternative bond liquidity measures, the percentage of non-zero bond returns, and bid-ask spreads. For each measure, we first calculate the liquidity measure at the bond level for all bonds issued by a firm, and then aggregate the bond level liquidity into firm level using the offering amount as the weight.<sup>13</sup> Both these measures and their estimation methods are based on Chen et al. (2007).

Our first liquidity measure reflects the proportion of days during which the bond traded. Because we do not have trading volume data, we use a day with no price change, i.e., zero returns, as a proxy for a non-traded day.<sup>14</sup> Since higher percentage of zero return indicates less liquidity, we use percentage of non-zero return days to capture liquidity. For each bond, we calculate the percentage of non-zero return (*%NON\_ZERO*) as the number of trading days with non-zero bond returns divided by the number of total trading days in a fiscal year.

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<sup>12</sup> We estimate a pooled OLS regression for a sample of 23,237 firm-year observations from 1995 to 2007. Consistent with the *FLOS* estimation procedure, we winsorize variables at top and bottom 1%. The adjusted  $R^2$  of the regression is 62%, suggesting that operating volatility explains a significant amount of the variation in *FLOS*.

<sup>13</sup> All bond level variables are aggregated into firm level in the same fashion except the offering amount, which is aggregated by taking the sum across all bonds.

<sup>14</sup> We use clean prices because gross prices include accrued interests that mechanically introduce price changes for every day.

Our second liquidity measure is based on the bid-ask spreads obtained from the Bloomberg Terminal. Bid-ask spread and its variants are widely used as liquidity measures in both the stock market (Roll, 1985) and the bond market (Chen et al., 2007). While Bloomberg provide bid and ask prices for various market makers, we collect the consensus quarterly quote because it provides the most comprehensive coverage. We calculate the quarterly spread as the ask price minus the bid price divided by the average of bid and ask price. Then we average the quarterly spread into the annual spread when there is at least one quarterly spread available for the year. To ensure that larger values correspond to higher level of liquidity, we multiply bid-ask spreads by -1 to get our second liquidity measure, *NEG\_BIDASK*. We express *NEG\_BIDASK* in percentages instead of basis points for the ease of interpretation of the coefficients in the regressions.

### 3.2.3. Cost of debt measure

We construct the cost of debt measure using the yield spreads (data item SP) from Datastream. Datastream defines spreads as the yield of a corporate bond minus the yield of the maturity matched Treasury bond.<sup>15</sup> Due to the difference in coverage of Datastream and Bloomberg, our two liquidity measures may be computed from different bonds issued by the same firm. To avoid biasing toward either set of bonds, we first compute the weighted average yield spreads separately for bonds used to calculate percentage of non-zero returns and for bonds used to calculate bid-ask spreads and take the weighted average of these two spreads as the firm's cost of debt measure, *YIELD\_SPREAD*, expressed in percentages.

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<sup>15</sup> When the maturities of the bonds for which the spread is calculated do not exactly match the maturity of the available government bonds, Datastream uses linear interpolation to estimate the yield of a government benchmark.

#### 3.2.4. *Control variables*

In the liquidity analysis, we control for three bond characteristics, age, offering amount and maturity.<sup>16</sup> Bond age has been documented to have a negative effect on liquidity since an increasing percentage of the issued bonds is held in buy-and-hold portfolios as the bond ages, thereby lowering the bond's liquidity (Sarig and Warga, 1989). Bonds of larger offering amount tend to be owned and analyzed by more investors and consequently have lower information costs and thus higher liquidity (Crabbe and Turner, 1995). Larger issues are also more likely to be traded, leading to higher liquidity. Although the effect of bond maturity on liquidity remains unclear empirically, we control for bond maturity because theoretical models predict that maturity structures are important to both bond issuers and bondholders (e.g. Brick and Ravid, 1985; Diamond, 1991).

We also control for a number of firm characteristics, including book-to-market ratio, leverage, number of analysts, size, ROA, and operating cash flow volatility. High book-to-market and high leverage may signal financial and operating risks that pose potential threats to bondholders, resulting in lower liquidity. Larger firms and firms with higher number of analysts following may have higher bond liquidity because of better information environment. Bonds issued by firms with higher ROA may trade with higher liquidity because of better firm performance. High operating cash flow volatility is usually associated with high risk and thereby lower liquidity. We note that another reason to control for operating cash flow volatility is that the accrual quality measure could simply be capturing operating volatility. We attempt to

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<sup>16</sup> We do not control for whether the bonds are secured with collaterals. While collateral requirements are important in evaluating risk at the bond level, our analyses are conducted at the firm level and whether one bond is secured at the expense of other bonds should not affect the perceived risk of the firm as a whole.

mitigate this concern both by using an adjusted *FLOS* measure (*ADJFLOS*) and by explicitly controlling for cash flow volatility in our regressions.

In the cost of debt analysis, we also control for similar bond and firm characteristics. The relation between bond age and yield spread is unclear. Newly issued bonds are likely to be underpriced so bond age may be negatively associated with yields (Houwelling et al., 2005). However, older bonds are in general less liquid and therefore bond age may also be positively associated with yield spread. We expect larger bonds to have lower cost of debt because issuers of large amount of bonds are generally financially healthy, and also because larger bonds are more liquid (Amihud and Mendelson, 1991; Houwelling et al., 2005). We don't have predictions for the effect of maturity on the cost of debt given the complex relation of maturity and liquidity noted before.

As for the firm characteristics, we expect a higher cost of debt for firms with larger book-to-market ratio, higher level of leverage, lower return on assets, and more volatile operating cash flows, since bondholders may perceive bonds issued by these firms as riskier and require higher premium. We expect that firm size and the number of analysts are negatively associated with the cost of debt since better information environments incur lower information costs to bondholders. In addition, following Bharath et al. (2008), we include the tangibility ratio and current ratio in the cost of debt model. Other things being equal, firms with more tangible assets and higher current ratios are less likely to default and therefore have lower cost of debt; therefore we expect both tangibility ratio and current ratio to have negative coefficients.

### 3.3. Descriptive statistics

#### 3.3.1. Statistical properties

Panel A of Table 2 reports descriptive statistics for the variables used in our analyses. The mean (median) *FLOS* (before multiplying by -1) is 0.033 (0.028) while Francis et al. (2005) report a mean (median) of 0.044 (0.031). Our sample firms have slightly higher accrual quality than reported in Francis et al. (2005), presumably because our sample consists of bond issuers that are generally large and financially healthy.<sup>17</sup>

In terms of the liquidity measures, the mean percentage non-zero return (*%NON\_ZERO*) is 77%, which means on average our sample firms have no price movements in 23% of the trading days. It is comparable to the statistics in Chen et al. (2007), which reports average percentage *zero* returns of 21%, or equivalently, average percentage *non-zero* returns of 79%. The median percentage non-zero return of our sample is 95%, indicating that the distribution of this liquidity measure is negatively skewed and there are some highly illiquid bonds in the sample. The mean *NEG\_BIDASK* of our sample firms is -0.42%, representing an average bid-ask spread of 0.42%. Chen et al. (2007) report an average bid-ask spread of 0.58% for a slightly different sample period. The mean (median) *YIELD\_SPREAD* is 1.85% (1.43%). As mentioned in footnote 8, our sample firms are larger (median total assets are \$8,063 million), more profitable (median return on assets is 0.10), and more highly leveraged (median leverage ratio is 0.46) than COMPUSTAT population because generally large and financially healthy firms are able to issue public debt.

#### 3.3.2. Correlations

Panel B of Table 2 presents the Pearson (above) and Spearman (below) correlations between variables. The two bond liquidity measures, *%NON\_ZERO* and *NEG\_BIDASK*, are

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<sup>17</sup> Note that high values of these measures before multiplying by -1 correspond to lower accrual quality.

significantly correlated with a Pearson (Spearman) correlation of 0.48 (0.37), lending support to the construct validity of the liquidity measures. The Pearson correlations between liquidity and accrual quality are positive and range from 0.12 (between *ADJFLOS* and *NEG\_BIDASK*) to 0.22 (between *FLOS* and *%NON\_ZERO*). This is consistent with our hypothesis that accrual quality is positively associated with liquidity. Cost of debt is negatively correlated with both accrual quality measures, consistent with findings in prior studies that firms with better accrual quality have lower cost of capital (Francis et al., 2005). Cost of debt is also negatively correlated with both liquidity proxies. Specifically, the Pearson correlation between *YIELD\_SPREAD* and *%NON\_ZERO* is -0.60 and that between *YIELD\_SPREAD* and *NEG\_BIDASK* is -0.43. This is consistent with an increasing body of literature suggesting that liquidity is a priced factor in the bond market (Houwelling et al., 2005; Longstaff et al., 2005; Chen et al., 2007). We note that the correlations between yield spread and liquidity are more than twice that of the correlations between yield spread and accrual quality, suggesting that liquidity has a higher order of effect on the cost of debt than accrual quality. Finally, various bond and firm characteristics are significantly correlated with liquidity and cost of debt in the expected directions.

#### 4. Accrual quality and bond liquidity

##### 4.1. Modeling liquidity

We hypothesize that *ceteris paribus*, firms with higher accrual quality have higher bond liquidity. We estimate the following regression to test this relation:

$$\begin{aligned}
 LIQUIDITY_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times LOGAGE_{j,t} + \beta_3 \times LOGMATURITY_{j,t} + \beta_4 \times LOGOFFER_{j,t} \\
 & + \beta_5 \times BM_{j,t} + \beta_6 \times LEV_{j,t} + \beta_7 \times LOGNUMAN_{j,t} + \beta_8 \times LOGSIZE_{j,t} + \beta_9 \times ROA_{j,t} \\
 & + \beta_{10} \times SDCFO_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t}
 \end{aligned}$$

where *LIQUIDITY* is either *%NON\_ZERO* or *NEG\_BIDASK* and *AQ* is either *FLOS* or *ADJFLOS*. A positive coefficient on *AQ* ( $\beta_1$ ) is consistent with our hypothesis that higher accrual quality is associated with higher bond liquidity. To control for the effects of outliers, we delete observations with absolute studentized residuals greater than two in all regressions.

We control for bond characteristics such as age (*LOGAGE*), maturity (*LOGMATURITY*), and offering amount (*LOGOFFER*). We also control for firm characteristics such as book-to-market ratio (*BM*), leverage (*LEV*), the number of analysts (*LOGNUMAN*), firm size (*LOGSIZE*), return on assets (*ROA*), and the standard deviation of operating cash flows (*SDCFO*). See section 3.2.4 for a discussion of our control variables. All control variables are defined in Table 1.

#### 4.2. Regression results

Table 3 reports the results of the liquidity regressions. Four models are generated from the combination of two liquidity measures and two accrual quality measures. In all four regressions, we find positive and significant coefficients on accrual quality. When the dependent variable is the percentage of non-zero bond returns (*%NON\_ZERO*), the coefficients of *AQ* are 2.61 (*FLOS* in Model 1) and 2.56 (*ADJFLOS* in Model 3), and both are significant at  $p < 0.01$ . The corresponding coefficients when the dependent variable is the bid-ask spread (*NEG\_BIDASK*) are 1.70 (*FLOS* in Model 2) and 1.95 (*ADJFLOS* in Model 4) respectively and both are also significant at  $p < 0.01$ . The positive impact of accrual quality on liquidity is economically significant. A movement from the 5<sup>th</sup> to 95<sup>th</sup> percentile in the *AQ* measures results in a predicted reduction in the proportion of non-trading days from 9.5% (*ADJFLOS* in Model 3) to 15.1% (*FLOS* in Model 1) and a predicted reduction in bid-ask spreads from 0.07% (*ADJFLOS* in Model 4) to 0.10% (*FLOS* in Model 2), which translates to a *relative* reduction in



bid-ask spreads of 17.2% to 23.5% for the average firm.<sup>18</sup> Overall, these results are consistent with our hypothesis that better accrual quality is associated with higher level of bond liquidity.

Consistent with prior studies, we find that bond age is negatively correlated with liquidity. The effects of bond maturity varies across models, increasing in the proportion of non-trading days but decreasing with the bid ask spreads. This attests to the complex relationship between maturity structure and bond liquidity. Bond offering amount is not related to liquidity, possibly because of its strong correlation with size. The firm characteristics appear to have the expected effects on bond liquidity. The book-to-market (*BM*), leverage (*LEV*), and the standard deviation of operating cash flows (*SDCFO*) are negatively associated with liquidity, confirming that higher risk leads to lower bond liquidity. The number of analysts following and firm size are positively associated with liquidity, consistent with that better information environment facilitates trading and enhances liquidity. Better firm performance (*ROA*) is associated with higher bond liquidity. Note that the effects of accrual quality on liquidity are significant after controlling for operating volatility (*SDCFO*), alleviating the concern that accrual quality may simply capture operational volatility.

## **5. Accrual quality and the cost of debt**

### *5.1. Modeling cost of debt*

The next question we ask is whether better accrual quality is associated with lower cost of debt and more importantly, whether this association occurs through the effect of accrual quality on bond liquidity. We estimate the following two models, respectively excluding and

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<sup>18</sup> To calculate the relative reduction in bid-ask spread, we divide the absolute reduction (0.07% for FLOS and 0.10% for ADJFLOS) by the mean bid-ask spread of our sample (0.42%).

including the liquidity proxies, to allow for a comparison of the coefficients on AQ with and without the effect of liquidity:

$$\begin{aligned} YIELD\_SPREAD_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times LOGAGE_{j,t} + \beta_3 \times LOGMATURITY_{j,t} \\ & + \beta_4 \times LOGOFFER_{j,t} + \beta_5 \times BM_{j,t} + \beta_6 \times CRATIO_{j,t} + \beta_7 \times LEV_{j,t} + \beta_8 \times LOGNUMAN_{j,t}, \\ & + \beta_9 \times LOGSIZE_{j,t} + \beta_{10} \times ROA_{j,t} + \beta_{11} \times SDCFO_{j,t} + \beta_{12} \times TANGIBLE_{j,t} + YearDummies \\ & + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

$$\begin{aligned} YIELD\_SPREAD_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times \%NON\_ZERO_{j,t} + \beta_3 \times NEG\_BIDASK_{j,t} \\ & + \beta_4 \times LOGAGE_{j,t} + \beta_5 \times LOGMATURITY_{j,t} + \beta_6 \times LOGOFFER_{j,t} + \beta_7 \times BM_{j,t} + \beta_8 \times CRATIO_{j,t} \\ & + \beta_9 \times LEV_{j,t} + \beta_{10} \times LOGNUMAN_{j,t} + \beta_{11} \times LOGSIZE_{j,t} + \beta_{12} \times ROA_{j,t} + \beta_{13} \times SDCFO_{j,t} \\ & + \beta_{14} \times TANGIBLE_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

where all variables are as defined in Table 1.

We include both liquidity measures, *%NON\_ZERO* and *NEG\_BIDASK*, in our cost of debt model since they may capture different dimensions of bond liquidity that are priced.<sup>19</sup> As in our liquidity model, we control for bond characteristics such as bond age, bond maturity, and offering amount, and firm characteristics such as book-to-market ratio, leverage, the number of analysts following the firm, firm size, return on assets, the standard deviation of operating cash flows, current ratio (*CRATIO*), and tangibility ratio (*TANGIBLE*). See section 4.2.3 for the discussion on how we expect these controls to affect the cost of debt.

## 5.2. Regression results

Table 4 presents the results of the cost of debt analysis. Without liquidity measures, the coefficients on *FLOS* and *ADJFLOS* are -5.53 and -5.57 respectively, and both are significant (see Models 1 and 3). This association is economically significant; for example, a move from 5% to 95% on the *FLOS* (*ADJFLOS*) variable lowers yield spreads by 0.32% (0.21%) in absolute

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<sup>19</sup> As a robustness check, we also analyze the effect of AQ on the cost of debt with only one liquidity measure in the model. The results of yield spread models that includes either *%NON\_ZERO* or *NEG\_BIDASK* are similar to those including both liquidity measures.

value, which corresponds to 15.4% (9.9%) reduction for the average firm in our sample. When liquidity measures are included, however, the coefficients on *FLOS* and *ADJFLOS* respectively drop to -2.68 and -2.70 and neither is statistically significant even at the 10% level. The reduction in coefficients on *FLOS* and *ADJFLOS* is significant both statistically and economically, constituting relative reductions of 52% for both. Overall, our results suggest that accrual quality is negatively associated with cost of debt, but much of this association arises through its association with liquidity—in fact, there is no reliable association between cost of debt and accrual quality after controlling for liquidity.

Of the three bond characteristics, only bond age significantly affects the cost of debt in the expected direction in all four models. The coefficients on bond age are significantly positive, consistent with findings in Amihud and Mendelson (1991) and Houwelling et al. (2005). The coefficients of bond maturity change from insignificant in the models without liquidity measures to significantly positive in the models with liquidity measures. The coefficients of bond offering amount are insignificant in all four models, probably because the effect of firm size dominates the effect of bond size. The firm characteristics, on the other hand, have expected signs in models both with and without liquidity, with the exception of the current ratio (*CRATIO*) and tangibility (*TANGIBLE*). As expected, high book-to-market ratio (*BM*), leverage (*LEV*), and the standard deviation of operating cash flows (*SDCFO*) are associated with high the cost of debt, while high firm performance (*ROA*), size (*LOGSIZE*), number of analysts (*LOGNUMAN*), and tangible assets (*TANGIBLE*) are associated with lower cost of debt. We note that the magnitude of the coefficients of the control variables appears to be larger in models without liquidity than that in models with liquidity. We expect *CRATIO* and *TANGIBLE* to have a negative effect on the cost of debt since higher value of these variables represents higher liquidity and higher ability

of the firms to repay debts. Table 4, however, reports positive coefficients of *CRATIO* and *TANGIBLE*. Although unexpected, the positive coefficient on *CRATIO* when bond spread is the dependent variable is also reported by Bharath et al. (2008). The positive coefficient on *TANGIBLE* is probably due to its multi-collinearity with the current ratio and operating volatility.

## 6. Additional analysis

### 6.1 Information asymmetry as an alternative explanation

Unlike related papers, we study liquidity as a distinct economic construct rather than a proxy for information asymmetry. We also argue that accrual quality could improve liquidity not only through reducing information asymmetry but also through reducing uncertainty. In order to verify whether our results are driven by information asymmetry or through other aspects of liquidity unrelated to information asymmetry, we replicate our analysis after controlling for information asymmetry. We control for information asymmetry by including *PIN* in our liquidity and cost-of-debt regressions. We note that *PIN* has been widely used as a proxy for information asymmetry (Easley et al., 2002 and 2004; Mohanram and Rajgopal, 2009).

We begin by examining the effect of controlling for information asymmetry in our liquidity regressions. Specifically, we estimate the following regression:

$$\begin{aligned} LIQUIDITY_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times PIN_{j,t} + \beta_3 \times LOGAGE_{j,t} + \beta_4 \times LOGMATURITY_{j,t} \\ & + \beta_5 \times LOGOFFER_{j,t} + \beta_6 \times BM_{j,t} + \beta_7 \times LEV_{j,t} + \beta_8 \times LOGNUMAN_{j,t} + \beta_9 \times LOGSIZE_{j,t} \\ & + \beta_{10} \times ROA_{j,t} + \beta_{11} \times SDCFO_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

Because we also include our information asymmetry proxy (*PIN*) in this regression, the coefficient on *AQ* ( $\beta_1$ ) captures the effect of accrual quality on liquidity that is independent of information asymmetry; this coefficient will be significant only when accrual quality affects

liquidity through some other dimensions that are orthogonal to information asymmetry. Panel A of Table 5 reports this regression's results. For brevity we only report coefficients on  $AQ$  ( $\beta_1$ ) and  $PIN$  ( $\beta_2$ ). First, we note that the  $PIN$  coefficient is significantly negative in all four specifications, consistent with information asymmetry contributing to bond illiquidity. Second, and more importantly, we find that the  $AQ$  coefficient continues to be significantly positive after  $PIN$  is included in all our specifications; in fact, the coefficient magnitudes are not significantly different to those when  $PIN$  is not included in the regression. These results suggest that much of the  $AQ$  and bond liquidity relation we document arises through channels unrelated to information asymmetry, which is consistent with our conjecture.

Next, we examine the effect of controlling for information asymmetry in the cost-of-debt regressions. In particular, we estimate the following two regressions:

$$\begin{aligned} YIELD\_SPREAD_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times PIN_{j,t} + \beta_3 \times LOGAGE_{j,t} + \beta_4 \times LOGMATURITY_{j,t} \\ & + \beta_5 \times LOGOFFER_{j,t} + \beta_6 \times BM_{j,t} + \beta_7 \times CRATIO_{j,t} + \beta_8 \times LEV_{j,t} + \beta_9 \times LOGNUMAN_{j,t} \\ & + \beta_{10} \times LOGSIZE_{j,t} + \beta_{11} \times ROA_{j,t} + \beta_{12} \times SDCFO_{j,t} + \beta_{13} \times TANGIBLE_{j,t} + YearDummies \\ & + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

$$\begin{aligned} YIELD\_SPREAD_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times \%NON\_ZERO_{j,t} + \beta_3 \times NEG\_BIDASK_{j,t} \\ & + \beta_4 \times PIN_{j,t} + \beta_5 \times LOGAGE_{j,t} + \beta_6 \times LOGMATURITY_{j,t} + \beta_7 \times LOGOFFER_{j,t} + \beta_8 \times BM_{j,t} \\ & + \beta_9 \times CRATIO_{j,t} + \beta_{10} \times LEV_{j,t} + \beta_{11} \times LOGNUMAN_{j,t} + \beta_{12} \times LOGSIZE_{j,t} + \beta_{13} \times ROA_{j,t} \\ & + \beta_{14} \times SDCFO_{j,t} + \beta_{15} \times TANGIBLE_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

As in our earlier analysis (Section 5), we estimate this regression separately without and with the inclusion of the two liquidity proxies ( $\%NON\_ZERO$  and  $NEG\_BIDASK$ ) and alternatively use  $FLOS$  and  $ADJFLOS$  as proxies for  $AQ$ . Because we include our information asymmetry proxy ( $PIN$ ) in this model, the coefficients on  $AQ$  ( $\beta_1$ ) and those on our two liquidity proxies ( $\beta_2$  and  $\beta_3$ ) capture the effects of accrual quality and liquidity respectively on cost of debt that are orthogonal to information asymmetry; these coefficients will be significant only when accrual quality and/or

liquidity affect cost of debt through some other dimensions that are independent of information asymmetry. We report the results of estimating this regression in Panel B of Table 5. We find that the inclusion of *PIN* in the regressions does not statistically (or economically) change any of the coefficients on either *AQ* or the liquidity proxies, nor does it change the difference in the *AQ* coefficients when liquidity gets included in the regression. Consequently, all the primary inferences from our earlier analysis generally carry through after controlling for *PIN*; specifically (1) the *AQ* coefficients are significantly negative before inclusion of liquidity proxies; (2) the inclusion of liquidity proxies results in a significant (both statistically and economically) reduction in the *AQ* coefficients; and (3) the *AQ* coefficients are not statistically significant after inclusion of liquidity proxies. These findings suggest that the liquidity-path through which accrual quality manifests in cost of debt does not arise through information asymmetry.

Surprisingly, *PIN* is not significantly related to cost of debt in these regressions (see Table 5 Panel B). The correlation matrix (Table 2 Panel B), however, reveals that *PIN* is significantly and positively correlated to cost of debt. Therefore, the most likely explanation for the insignificant *PIN* coefficients is that other control variables (such as firm size and number of analysts) may be capturing aspects of information asymmetry that is reflected in the *PIN*s. Besides this explanation, it is possible that our sample—which comprises large and stable firms that have issued bonds—may have both lower information asymmetry and lower variation in information asymmetry than earlier studies that have used *PIN* in stock market settings.<sup>20</sup> Finally, it is also possible that information asymmetry is a relatively smaller component of bond liquidity than stock liquidity, because inventory cost and search cost are relatively more

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<sup>20</sup> Comparing our descriptive statistics of *PIN* to those reported in Duarte and Young (2009) reveals that our sample firms have much lower *PIN* than the sample firms in Duarte and Young (2009). For example, we report a median *PIN* of 0.10 while Duarte and Young (2009) report a median of 0.20. In addition, our 5<sup>th</sup> (95<sup>th</sup>) percentile is 0.03 (0.21) while theirs is 0.10 (0.51), suggesting much lower variation in *PIN* in our sample.

important for bond liquidity and bond illiquidity is less concentrated in the smallest firms than stock illiquidity.<sup>21</sup>

## 6.2 The role of credit ratings

Most studies examining cost of debt control for credit ratings, which are used as an all-inclusive proxy for credit risk (Chen et al., 2007; Jiang, 2008). In our primary analysis, however, we do not control for credit ratings. The reason is that we are interested in the underlying structural relations among accrual quality, liquidity and cost of debt independent of whether these relations are anticipated by credit raters and reflected in their ratings. Put differently, we attempt to avoid a situation where we conclude that accrual quality is not related to bond liquidity and/or cost of debt, not because indeed there is no underlying relation, but because finding this relation is preempted by controlling for credit ratings which reflect this relation.

To examine the complex relations among credit ratings, accrual quality, liquidity, and the cost of debt, we conduct several levels of analysis. First, we model ratings as a function of accrual quality and then we add liquidity to the model to gauge whether ratings reflect the effect of accrual quality on improving liquidity and thus indirectly affect credit risk through liquidity. Specifically, we run the following two regressions:

$$\begin{aligned} RATING_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times LOGAGE_{j,t} + \beta_3 \times LOGMATURITY_{j,t} + \beta_4 \times LOGOFFER_{j,t} \\ & + \beta_5 \times BM_{j,t} + \beta_6 \times CRATIO_{j,t} + \beta_7 \times LEV_{j,t} + \beta_8 \times LOGNUMAN_{j,t} + \beta_9 \times LOGSIZE_{j,t} \\ & + \beta_{10} \times ROA_{j,t} + \beta_{11} \times SDCFO_{j,t} + \beta_{12} \times TANGIBLE_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

$$\begin{aligned} RATING_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times \%NON\_ZERO_{j,t} + \beta_3 \times NEG\_BIDASK_{j,t} + \beta_4 \times LOGAGE_{j,t} \\ & + \beta_5 \times LOGMATURITY_{j,t} + \beta_6 \times LOGOFFER_{j,t} + \beta_7 \times BM_{j,t} + \beta_8 \times CRATIO_{j,t} + \beta_9 \times LEV_{j,t} \\ & + \beta_{10} \times LOGNUMAN_{j,t} + \beta_{11} \times LOGSIZE_{j,t} + \beta_{12} \times ROA_{j,t} + \beta_{13} \times SDCFO_{j,t} + \beta_{14} \times TANGIBLE_{j,t} \\ & + YearDummies + IndustryDummies + \varepsilon_{j,t} \end{aligned}$$

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<sup>21</sup> We also run a robustness test by including the decomposed PIN as in Duarte and Young (2009). Not surprisingly, the PIN that is related to liquidity is significant in explaining liquidity, but not the PIN that is related to information asymmetry. In addition, both PIN components are insignificant in the cost of debt regression, consistent with that our liquidity measures dominate PIN in capturing bond liquidity.

We define ratings as the natural log of the categorical variable ranging from 1 to 9 where 1 corresponds to the worst S&P rating (C) and 9 corresponds to the best S&P rating (AAA).<sup>22</sup> Larger values of our rating's variable represent more favorable ratings. The first four columns of Table 6 report the results of these two regressions (using *FLOS* and *ADJFLOS* as alternative AQ proxies). We find that the relation between credit ratings and accrual quality/liquidity is similar to the relation between cost of debt and accrual quality/liquidity. Specifically, we find that (1) the AQ coefficients are significantly positive before inclusion of liquidity proxies; (2) the inclusion of liquidity proxies results in a significant (both statistically and economically) reduction in the magnitude of the AQ coefficients; and (3) the AQ coefficients are not statistically significant after inclusion of liquidity proxies. Overall, we find that credit ratings incorporate the complex relations between accrual quality, liquidity and credit risk, in particular, that much of the effect of accrual quality on credit ratings arises through its effect on liquidity.

We next explore whether the credit ratings *fully* incorporate the triangular relation between accrual quality, liquidity and cost of debt by estimating our original cost-of-debt regressions after including credit rating in the model. Specifically, we estimate the following two regressions, where the first excludes and the second includes the liquidity proxies:

$$\begin{aligned}
YIELD\_SPREAD_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times LOGAGE_{j,t} + \beta_3 \times LOGMATURITY_{j,t} \\
& + \beta_4 \times LOGOFFER_{j,t} + \beta_5 \times LOGRATING_{j,t} + \beta_6 \times BM_{j,t} + \beta_7 \times CRATIO_{j,t} + \beta_8 \times LEV_{j,t} \\
& + \beta_9 \times LOGNUMAN_{j,t} + \beta_{10} \times LOGSIZE_{j,t} + \beta_{11} \times ROA_{j,t} + \beta_{12} \times SDCFO_{j,t} + \beta_{13} \times TANGIBLE_{j,t} \\
& + YearDummies + IndustryDummies + \varepsilon_{j,t}
\end{aligned}$$

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<sup>22</sup> We transform credit ratings in this manner because they have a non-linear relation with cost of debt. Specifically, differences in bond yield spreads across the higher, i.e., more favorable, rating categories are much narrower than those in the lower categories. Our transformation is expected to linearize this relation to a large extent. To verify this, we graph yield spreads and our log transformed ratings and find an almost linear correspondence between the two.



$$\begin{aligned}
YIELD\_SPREAD_{j,t} = & \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times \%NON\_ZERO_{j,t} + \beta_3 \times NEG\_BIDASK_{j,t} \\
& + \beta_4 \times LOGAGE_{j,t} + \beta_5 \times LOGMATURITY_{j,t} + \beta_6 \times LOGOFFER_{j,t} + \beta_7 \times LOGRATING_{j,t} \\
& + \beta_8 \times BM_{j,t} + \beta_9 \times CRATIO_{j,t} + \beta_{10} \times LEV_{j,t} + \beta_{11} \times LOGNUMAN_{j,t} + \beta_{12} \times LOGSIZE_{j,t} \\
& + \beta_{13} \times ROA_{j,t} + \beta_{14} \times SDCFO_{j,t} + \beta_{15} \times TANGIBLE_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t}
\end{aligned}$$

If ratings fully incorporate the effect of accrual quality and liquidity on cost of debt, then we expect ratings to dominate accrual quality *and* liquidity in explaining the cost of debt. The last four columns of Table 6 report result from these regressions (alternatively using *FLOS* and *ADJFLOS* as proxies for AQ). We find that after controlling for ratings, accrual quality and liquidity continue to explain cost of debt and there is a significant drop in the AQ coefficients after liquidity is included. This suggests that ratings do not fully incorporate the triangular relation between accrual quality, liquidity and cost of debt. Interestingly, the decline in the AQ coefficients after the inclusion of liquidity (40% drop for *FLOS* and 35% for *ADJFLOS*) is not as large as the decline without ratings reported in Table 4 (52% for both *FLOS ADJFLOS*) and the differences between the declines is statistically significant for *FLOS*. Despite these subtle differences, the inclusion of credit ratings does not qualitatively alter any of our primary inferences regarding the underlying structural relations among accounting quality, bond liquidity and cost of debt.

## 7. Conclusion

We examine the association between accrual quality and bond liquidity and the implications of this association for understanding the effect of accrual quality on the cost of debt. We show that accrual quality is positively associated with bond liquidity. We also show that the documented negative relation between accrual quality and cost of debt (Francis et al., 2005) is largely explained by the association of accounting quality with liquidity. Our results are robust to

controlling for information asymmetry (through PIN), suggesting that liquidity components unrelated to information asymmetry are driving our results. We also show that credit ratings reflect the underlying structural relations among accrual quality, bond liquidity and cost of debt, albeit in an incomplete/imperfect manner.

We are the first to examine the role of accrual quality in improving bond liquidity. We also propose an alternative path through which accrual quality manifests in cost of debt, i.e., through its effect on bond liquidity. Unlike much of the prior literature we study liquidity as a distinct economic construct rather than as a surrogate for information asymmetry. Our results emphasize the importance of examining the role of accrual quality in improving bond liquidity and the importance of this for understanding how accrual quality manifests in lower cost of debt. The results in this paper improve our understanding of the complex effects of accrual quality in the bond markets, and highlight the need to further study the role of accounting information in the debt markets.

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**Figure 1**  
**Distributions of the Percentage of Zero Returns of Bonds and Stocks by Total Assets**

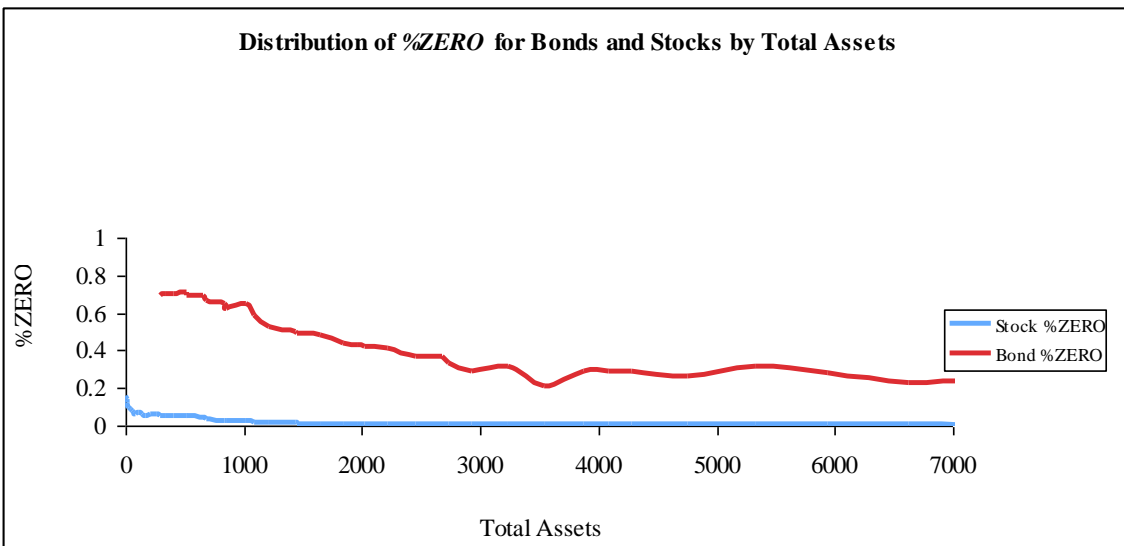


Figure 1 illustrates the difference in distributional properties between bond illiquidity and stock illiquidity. It presents the distribution of percentage zero returns for bonds and stocks by firm size (total assets in \$ millions). The X axis is firms' total assets (AT in COMPUSTAT) at the end of the fiscal year. The Y axis represents the *illiquidity* measure – the percentage of trading days with zero return (no change in prices) in a fiscal year (see Chen et al. (2007) for a discussion of the percentage zero bond returns; see Liu (2006) for a discussion of the percentage zero stock returns). The percentage of zero bond returns is 1 minus %NON\_ZERO calculated in Section 3.2.2. We follow Liu (2006) to compute the percentage zero stock returns for firms with December fiscal year end.

**Table 1**  
**Variable Definitions**

VARIABLE	DEFINITION
<b>Accrual quality</b>	
<i>FLOS</i>	Accrual quality measure as developed in Francis et al. (2005), which is the residuals from the cross-sectional regressions of current accruals on past, current, and future cash flows from operations, calculated over ten-year rolling window. We multiple this measure by -1 so that larger values of <i>FLOS</i> represent better accrual quality. Cash flows from operations are calculated as income before extraordinary items (IB in COMPUSTAT) plus depreciation and amortization (DP in COMPUSTAT) minus current accruals, which are the sum of changes in current assets (ACT in COMPUSTAT), cash and short-term investment (CHE in COMPUSTAT), current liabilities (LCT in COMPUSTAT), debt in current liabilities (DLC in COMPUSTAT), scaled by the beginning assets of the year.
<i>ADJFLOS</i>	Accrual quality measure based on <i>FLOS</i> , adjusted for accrual volatilities. It is calculated as the residuals from the regressions of <i>FLOS</i> on the standard deviations of current accruals estimated over the same ten-year rolling window for a sample of 23,237 firm-year observations in COMPUSTAT in non-utility or financial industries from 1995 to 2007. Larger values of <i>ADJFLOS</i> represent better accrual quality. Current accruals are calculated as the sum of changes in current assets (ACT in COMPUSTAT), cash and short-term investment (CHE in COMPUSTAT), current liabilities (LCT in COMPUSTAT), and debt in current liabilities (DLC in COMPUSTAT), scaled by the beginning assets of the year.
<b>Bond Liquidity and Cost of Debt</b>	
<i>%NON_ZERO</i>	Our first firm liquidity measure, calculated as the number of trading days with non-zero bond returns as a percentage of total trading days, aggregated from bond level to firm level using bond offering amount as the weight. Larger values of <i>%NON_ZERO</i> represent higher levels of liquidity.
<i>NEG_BIDASK</i>	Our second firm liquidity measure, calculated as the average of bid ask spreads across bonds issued by the firm, weighed by offering amount. Bid ask spreads are expressed in percentages. We multiply this measure by -1 so that larger values of <i>NEG_BIDASK</i> represent higher levels of liquidity.
<i>YIELD_SPREAD</i>	Cost of debt in percentage, which is the weighted average yield spread of all bonds issued by the firm. Individual bond yield spreads are bond yields over the yields of the Treasury bill of the same maturity, obtained from Datastream (data item <i>sp</i> ). Larger values of <i>YIELD_SPREAD</i> represent higher cost of debt.
<b>Bond Characteristics</b>	
<i>AGE</i>	Bond age (in the number of years) calculated as the weighted average bond age across bonds issued by the firm, using offering amounts as weights. Individual bond age is one plus the number of years from bond offering date to the end of the fiscal year.
<i>LOGAGE</i>	Logarithm of <i>AGE</i> .

<i>MATURITY</i>	Bond maturity (in the number of years) calculated as the weighted average bond maturity across bonds issued by the firm, using offering amounts as weights. Individual bond maturity is one plus the number of years from bond offering date to bond maturity date.
<i>LOGMATURITY OFFER</i>	Logarithm of <i>MATURITY</i> . Total offering amount, which is the sum of offering amount of bonds issued by the firm.
<i>LOGOFFER</i>	Logarithm of <i>OFFER</i> .
<i>RATING</i>	The most recent S&P credit rating of individual bonds from FISD, translated into numerals with smaller values indicating better credit ratings (grade AAA corresponding to 1; grade C corresponding to 21). Firm ratings are then calculated as the weighted average bond rating across bonds issued by the firm, using offering amounts as weights and rounded to the nearest whole number. <i>RATING</i> is a 9-level categorical variable: Rating = 1 if firm ratings =21 (C); Rating = 2 if firm ratings =20 (CC); Rating=3 if firm ratings between 17 (CCC+) to 19 (CCC-); Rating=4 if firm ratings between 14 (B+) to 16 (B-); Rating=5 if firm ratings between 11 (BB+) to 13 (BB-); Rating=6 if firm ratings between 8 (BBB+) to 10 (BBB-); Rating=7 if firm ratings between 5 (A+) to 7 (A-); Rating=8 if firm ratings between 2 (AA+) to 4 (AA-); Rating = 9 if firm ratings =1 (AAA). Higher values of <i>RATING</i> indicate better credit rating.
<i>LOGRATING</i>	Logarithm of <i>RATING</i> .

### **Firm Characteristics**

<i>BM</i>	Book-to-market ratio calculated as the book value of equity (CEQ in COMPUSTAT) over the market value of equity (CSHO*PRCC_F in COMPUSTAT).
<i>CRATIO</i>	Current ratio calculated as current assets (ACT in COMPUSTAT) divided by current liabilities (LCT in COMPUSTAT) at the end of year.
<i>LEV</i>	Leverage calculated as the sum of current liabilities (LCT in COMPUSTAT) and long-term debt (DLTT in COMPUSTAT) over total assets (AT in COMPUSTAT) at the end of year.
<i>NUMAN</i>	One plus the number of analysts issuing an annual forecast for the firm in the fiscal year, collected from the I/B/E/S database.
<i>LOGNUMAN</i>	Logarithm of <i>NUMAN</i> .
<i>PIN</i>	Probability of informed trading. The PIN estimates are obtained from Professor Young (Duarte and Young 2009) for 735 observations in our sample. The rest are estimated as in “Time-varying arrival rates of informed and uninformed trades” (2008) by Easley, Engle, O’Hara, and Wu.
<i>ROA</i>	Return on assets calculated as operating income (OIADP in COMPUSTAT) over average total assets (AT in COMPUSTAT) for the year.
<i>SDACCR</i>	Standard deviation of current accruals over ten year rolling window. Current accruals are calculated as the sum of changes in current assets (ACT in COMPUSTAT), cash and short-term investment (CHE in COMPUSTAT), current liabilities (LCT in COMPUSTAT), and debt in current liabilities (DLC in COMPUSTAT), scaled by the beginning assets of the year.
<i>SDCFO</i>	Standard deviation of cash flows from operations over the ten year rolling window. Cash flows from operations are calculated as income before extraordinary items



	(IB in COMPUSTAT) plus depreciation and amortization (DP in COMPUSTAT) minus current accruals.
<i>SIZE</i>	Total assets (AT in COMPUSTAT) at the end of the fiscal year.
<i>LOGSIZE</i>	Logarithm of <i>SIZE</i> .
<i>TANGIBLE</i>	Tangibility ratio calculated as net property, plant, and equipment (PPENT in COMPUSTAT) divided by total assets (AT in COMPUSTAT) at the end of the year.

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**Table 2**  
**Summary Statistics of the Sample Firms**

**Panel A. Descriptive Statistics**

<b>VARIABLE</b>	<b>MEAN</b>	<b>MEDIAN</b>	<b>STDDEV</b>	<b>5%</b>	<b>95%</b>
<b>Accrual quality</b>					
<i>FLOS</i>	-0.033	-0.028	0.018	-0.071	-0.013
<i>ADJFLOS</i>	0.006	0.009	0.011	-0.016	0.021
<b>Bond Liquidity and Cost of Debt</b>					
<i>%NON_ZERO</i>	0.77	0.95	0.30	0.10	0.96
<i>NEG_BIDASK (%)</i>	-0.42	-0.37	0.19	-0.86	-0.22
<i>YIELD_SPREAD (%)</i>	1.85	1.43	1.26	0.63	4.52
<b>Bond Characteristics</b>					
<i>AGE</i>	5.12	4.84	2.59	1.50	9.95
<i>MATURITY</i>	17.36	15.61	8.40	8.50	31.00
<i>OFFER (\$mils)</i>	1,351.22	715.94	1,609.34	150.00	4,811.43
<i>RATING</i>	6.18	6.00	1.00	4.00	8.00
<i>LOGRATING</i>	1.81	1.79	0.17	1.39	2.08
<b>Firm Characteristics</b>					
<i>BM</i>	0.46	0.41	0.26	0.14	0.96
<i>CRATIO</i>	1.51	1.38	0.69	0.61	2.82
<i>LEV</i>	0.47	0.46	0.12	0.26	0.70
<i>NUMAN</i>	20.54	19.00	11.07	5.00	40.00
<i>PIN</i>	0.11	0.10	0.06	0.03	0.21
<i>ROA</i>	0.11	0.10	0.06	0.02	0.22
<i>SDCFO</i>	0.04	0.03	0.03	0.01	0.10
<i>SDACCR</i>	0.06	0.05	0.03	0.02	0.12
<i>SIZE (\$mils)</i>	14,610.68	8,062.63	18,371.04	1,349.03	44,560.00
<i>TANGIBLE</i>	0.39	0.33	0.25	0.08	0.85

Panel A Table 2 presents the descriptive statistics of the main variables for the sample of 1,310 observations from 1995 to 2007. We winsorize the firm characteristics at 1% and 99% of the distribution. We report the mean, median, standard deviation, 5% and 95% of the distribution.

See Table 1 for variable definitions.

\**NEG\_BIDASK* is negative because we multiply bond bid ask spreads by -1 to make large values represent better liquidity.

**Table 2 (Cont'd)**

**Panel B. Pearson (above) and Spearman (below) Correlations ( $p$  values in parentheses)**

<b>VAR</b>	<b>FLOS</b>	<b>ADJFL OS</b>	<b>%NON_ ZERO</b>	<b>NEG_B IDASK</b>	<b>YIELD_ SPREA D</b>	<b>AGE</b>	<b>MATURI TY</b>	<b>OFFER</b>	<b>LOGRA TING</b>	<b>BM</b>	<b>CRATIO</b>	<b>LEV</b>	<b>NUMAN</b>	<b>PIN</b>	<b>ROA</b>	<b>SDACCR</b>	<b>SDCFO</b>	<b>SIZE</b>	<b>TANGIB LE</b>
<b>FLOS</b>	1	0.71 (0.00)	0.22 (0.00)	0.13 (0.00)	-0.25 (0.00)	0.10 (0.00)	0.18 (0.00)	0.03 (0.22)	0.22 (0.00)	-0.01 (0.75)	-0.25 (0.00)	-0.26 (0.00)	0.13 (0.00)	-0.02 (0.50)	0.03 (0.23)	-0.75 (0.00)	-0.57 (0.00)	0.05 (0.05)	0.40 (0.00)
<b>ADJFL LOS</b>	0.73 (0.00)	1	0.12 (0.00)	0.12 (0.00)	-0.14 (0.00)	-0.02 (0.57)	0.02 (0.38)	-0.05 (0.07)	0.08 (0.01)	0.01 (0.85)	-0.05 (0.06)	-0.10 (0.00)	0.04 (0.13)	0.04 (0.14)	0.08 (0.00)	-0.07 (0.01)	-0.15 (0.00)	-0.05 (0.05)	0.14 (0.00)
<b>%NON_ ZER</b>	0.17 (0.00)	0.10 (0.00)	1	0.48 (0.00)	-0.60 (0.00)	0.11 (0.00)	0.12 (0.00)	0.17 (0.00)	0.55 (0.00)	-0.21 (0.00)	-0.14 (0.00)	-0.18 (0.00)	0.21 (0.00)	-0.24 (0.00)	0.15 (0.00)	-0.21 (0.00)	-0.20 (0.00)	0.19 (0.00)	-0.01 (0.84)
<b>NEG_ BIDAS</b>	0.08 (0.01)	0.09 (0.00)	0.37 (0.00)	1	-0.43 (0.00)	-0.01 (0.64)	-0.06 (0.02)	0.10 (0.00)	0.44 (0.00)	-0.15 (0.00)	-0.12 (0.00)	-0.17 (0.00)	0.13 (0.00)	-0.16 (0.00)	0.20 (0.00)	-0.09 (0.00)	-0.11 (0.00)	0.13 (0.00)	-0.07 (0.01)
<b>YIELD_ SPRE</b>	-0.25 (0.00)	-0.15 (0.00)	-0.54 (0.00)	-0.41 (0.00)	1	-0.08 (0.00)	-0.09 (0.00)	-0.17 (0.00)	-0.69 (0.00)	0.45 (0.00)	0.15 (0.00)	0.30 (0.00)	-0.30 (0.00)	0.24 (0.00)	-0.41 (0.00)	0.25 (0.00)	0.27 (0.00)	-0.26 (0.00)	0.04 (0.14)
<b>AGE</b>	0.14 (0.00)	0.04 (0.11)	0.15 (0.00)	-0.01 (0.75)	-0.12 (0.00)	1	0.46 (0.00)	0.04 (0.15)	0.10 (0.00)	0.02 (0.56)	0.02 (0.56)	-0.19 (0.00)	0.08 (0.00)	-0.13 (0.00)	0.04 (0.20)	-0.15 (0.00)	-0.16 (0.00)	0.18 (0.00)	0.04 (0.17)
<b>MATU RITY</b>	0.27 (0.00)	0.09 (0.00)	0.06 (0.03)	-0.12 (0.00)	-0.04 (0.13)	0.47 (0.00)	1	0.10 (0.00)	0.29 (0.00)	-0.00 (0.88)	-0.17 (0.00)	-0.10 (0.00)	0.29 (0.00)	-0.06 (0.04)	0.06 (0.02)	-0.22 (0.00)	-0.18 (0.00)	0.25 (0.00)	0.21 (0.00)
<b>OFFE R</b>	0.13 (0.00)	0.03 (0.33)	0.09 (0.00)	0.01 (0.71)	-0.22 (0.00)	0.09 (0.00)	0.25 (0.00)	1	0.14 (0.00)	0.00 (0.99)	-0.21 (0.00)	0.01 (0.70)	0.24 (0.00)	-0.28 (0.00)	-0.06 (0.03)	-0.09 (0.00)	-0.08 (0.00)	0.58 (0.00)	0.05 (0.06)
<b>LOGR ATING</b>	0.25 (0.00)	0.12 (0.00)	0.41 (0.00)	0.28 (0.00)	-0.67 (0.00)	0.11 (0.00)	0.31 (0.00)	0.17 (0.00)	1	-0.37 (0.00)	-0.14 (0.00)	-0.26 (0.00)	0.36 (0.00)	-0.21 (0.00)	0.35 (0.00)	-0.24 (0.00)	-0.31 (0.00)	0.39 (0.00)	-0.06 (0.02)
<b>BM</b>	0.04 (0.14)	0.04 (0.20)	-0.16 (0.00)	-0.15 (0.00)	0.39 (0.00)	-0.01 (0.60)	0.03 (0.32)	0.01 (0.80)	-0.44 (0.00)	1	0.06 (0.02)	-0.09 (0.00)	-0.20 (0.00)	0.12 (0.00)	-0.53 (0.00)	0.01 (0.75)	0.02 (0.37)	-0.04 (0.11)	0.14 (0.00)
<b>CRATI O</b>	-0.27 (0.00)	-0.05 (0.10)	-0.03 (0.22)	-0.01 (0.85)	0.10 (0.00)	-0.02 (0.55)	-0.23 (0.00)	-0.24 (0.00)	-0.10 (0.00)	0.03 (0.23)	1	-0.15 (0.00)	-0.22 (0.00)	0.04 (0.14)	0.04 (0.16)	0.29 (0.00)	0.19 (0.00)	-0.28 (0.00)	-0.38 (0.00)
<b>LEV</b>	-0.25 (0.00)	-0.11 (0.00)	-0.16 (0.00)	-0.15 (0.00)	0.27 (0.00)	-0.18 (0.00)	-0.12 (0.00)	0.03 (0.32)	-0.20 (0.00)	-0.13 (0.00)	-0.10 (0.00)	1	-0.21 (0.00)	0.16 (0.00)	-0.14 (0.00)	0.29 (0.00)	0.11 (0.00)	-0.14 (0.00)	-0.16 (0.00)
<b>NUMA N</b>	0.18 (0.00)	0.07 (0.01)	0.13 (0.00)	0.06 (0.02)	-0.29 (0.00)	0.10 (0.00)	0.35 (0.00)	0.34 (0.00)	0.38 (0.00)	-0.21 (0.00)	-0.26 (0.00)	-0.19 (0.00)	1	-0.23 (0.00)	0.22 (0.00)	-0.13 (0.00)	0.07 (0.01)	0.44 (0.00)	0.21 (0.00)
<b>PIN</b>	-0.04 (0.15)	-0.02 (0.54)	-0.24 (0.00)	-0.14 (0.00)	0.31 (0.00)	-0.19 (0.00)	-0.11 (0.00)	-0.42 (0.00)	-0.27 (0.00)	0.23 (0.00)	0.07 (0.01)	0.17 (0.00)	-0.35 (0.00)	1	-0.13 (0.00)	0.07 (0.01)	0.01 (0.70)	-0.25 (0.00)	0.03 (0.23)
<b>ROA</b>	0.05 (0.05)	0.08 (0.00)	0.18 (0.00)	0.20 (0.00)	-0.42 (0.00)	0.05 (0.07)	0.03 (0.33)	-0.05 (0.07)	0.39 (0.00)	-0.57 (0.00)	-0.00 (0.98)	-0.13 (0.00)	0.24 (0.00)	-0.19 (0.00)	1	0.02 (0.41)	-0.01 (0.72)	0.03 (0.27)	-0.03 (0.29)
<b>SDAC CR</b>	-0.81 (0.00)	-0.28 (0.00)	-0.16 (0.00)	-0.04 (0.17)	0.22 (0.00)	-0.18 (0.00)	-0.31 (0.00)	-0.17 (0.00)	-0.25 (0.00)	-0.06 (0.03)	0.35 (0.00)	0.30 (0.00)	-0.19 (0.00)	0.05 (0.11)	0.01 (0.67)	1	0.68 (0.00)	-0.13 (0.00)	-0.41 (0.00)
<b>SDCF O</b>	-0.60 (0.00)	-0.29 (0.00)	-0.19 (0.00)	-0.08 (0.00)	0.27 (0.00)	-0.16 (0.00)	-0.23 (0.00)	-0.08 (0.00)	-0.34 (0.00)	0.01 (0.60)	0.21 (0.00)	0.09 (0.00)	0.02 (0.58)	0.01 (0.70)	-0.03 (0.24)	0.63 (0.00)	1	-0.07 (0.01)	-0.15 (0.00)
<b>SIZE</b>	0.20 (0.00)	0.05 (0.06)	0.17 (0.00)	0.05 (0.10)	-0.37 (0.00)	0.26 (0.00)	0.47 (0.00)	0.70 (0.00)	0.46 (0.00)	-0.09 (0.00)	-0.38 (0.00)	-0.16 (0.00)	0.61 (0.00)	-0.47 (0.00)	0.05 (0.10)	-0.25 (0.00)	-0.15 (0.00)	1	0.01 (0.82)
<b>TANGI BLE</b>	0.39 (0.00)	0.14 (0.00)	-0.05 (0.10)	-0.12 (0.00)	0.07 (0.01)	0.06 (0.03)	0.30 (0.00)	0.09 (0.00)	-0.05 (0.10)	0.17 (0.00)	-0.40 (0.00)	-0.14 (0.00)	0.20 (0.00)	0.05 (0.11)	-0.04 (0.19)	-0.45 (0.00)	-0.16 (0.00)	0.10 (0.00)	1

**Table 3**  
**Accrual quality and Bond Liquidity**

$$LIQUIDITY_{j,t} = \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times LOGAGE_{j,t} + \beta_3 \times LOGMATURITY_{j,t} + \beta_4 \times LOGOFFER_{j,t} + \beta_5 \times BM_{j,t} + \beta_6 \times LEV_{j,t} + \beta_7 \times LOGNUMAN_{j,t} + \beta_8 \times LOGSIZE_{j,t} + \beta_9 \times ROA_{j,t} + \beta_{10} \times SDCFO_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t}$$

Variable	Predicted Sign	FLOS		ADJFLOS	
		Model1	Model2	Model3	Model4
		%NON_ZERO	NEG_BIDASK	%NON_ZERO	NEG_BIDASK
Intercept		0.23 (0.10)	-0.56 (0.00)	0.17 (0.22)	-0.57 (0.00)
AQ	+	2.61 (0.00)	1.70 (0.00)	2.56 (0.00)	1.95 (0.00)
LOGAGE	-	-0.04 (0.04)	-0.04 (0.00)	-0.03 (0.07)	-0.04 (0.00)
LOGMATURITY	?	0.08 (0.00)	-0.05 (0.01)	0.09 (0.00)	-0.05 (0.01)
LOGOFFER	+	-0.01 (0.28)	-0.01 (0.33)	-0.01 (0.35)	-0.01 (0.31)
BM	-	-0.05 (0.12)	-0.01 (0.63)	-0.06 (0.08)	-0.01 (0.82)
LEV	-	-0.16 (0.05)	-0.08 (0.18)	-0.21 (0.01)	-0.10 (0.13)
LOGNUMAN	+	0.07 (0.00)	0.02 (0.19)	0.07 (0.00)	0.02 (0.10)
LOGSIZE	+	0.05 (0.00)	0.04 (0.00)	0.05 (0.00)	0.04 (0.00)
ROA	+	0.71 (0.00)	0.74 (0.00)	0.59 (0.00)	0.71 (0.00)
SDCFO	-	-0.60 (0.04)	0.05 (0.77)	-1.19 (0.00)	-0.59 (0.00)
Year and Industry Dummies		Yes	Yes	Yes	Yes
N		1,220	1,278	1,223	1,276
Adjusted R-square		59.78%	32.16%	59.18%	32.84%

Table 3 reports results of the liquidity regressions, with two-sided  $p$  values (based on cluster corrected standard errors) reported in parentheses below the coefficients. The sample contains 1,310 firm-year observations from the year 1995 to 2007. To control the effects of outliers, we delete observations with absolute studentized residuals greater than two. This outlier control technique causes slightly different numbers of observations for different model. Liquidity is proxied by %NON\_ZERO in Model 1 and 3, and NEG\_BIDASK in Model 2 and 4. Accrual quality is proxied by FLOS in Model 1 and 2, and ADJFLOS in Model 3 and 4. See Table 1 for variable definitions.

**Table 4**  
**Accrual quality and Cost of Debt**

$$YIELD\_SPREAD_{j,t} = \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times \%NON\_ZERO_{j,t} + \beta_3 \times NEG\_BIDASK_{j,t} + \beta_4 \times LOGAGE_{j,t} + \beta_5 \times LOGMATURITY_{j,t} + \beta_6 \times LOGOFFER_{j,t} + \beta_7 \times BM_{j,t} + \beta_8 \times CRATIO_{j,t} + \beta_9 \times LEV_{j,t} + \beta_{10} \times LOGNUMAN_{j,t} + \beta_{11} \times LOGSIZE_{j,t} + \beta_{12} \times ROA_{j,t} + \beta_{13} \times SDCFO_{j,t} + \beta_{14} \times TANGIBLE_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t}$$

Variable	Predicted Sign	FLOS		ADJFLOS	
		Model1	Model2	Model3	Model4
		W/O LIQ	W LIQ	W/O LIQ	W LIQ
Intercept		2.69 (0.00)	2.75 (0.00)	2.84 (0.00)	2.82 (0.00)
AQ	-	-5.53 (0.03)	-2.68 (0.18)	-5.57 (0.07)	-2.70 (0.26)
DIFF			-2.85 (0.03)		-2.87 (0.07)
%NON_ZERO	-		-1.36 (0.00)		-1.36 (0.00)
NEG_BIDASK	-		-0.58 (0.00)		-0.58 (0.00)
LOGAGE	+	0.24 (0.00)	0.16 (0.00)	0.24 (0.00)	0.16 (0.00)
LOGMATURITY	?	0.06 (0.51)	0.14 (0.05)	0.06 (0.51)	0.14 (0.05)
LOGOFFER	-	-0.03 (0.53)	-0.05 (0.16)	-0.03 (0.54)	-0.05 (0.17)
BM	+	1.08 (0.00)	0.96 (0.00)	1.09 (0.00)	0.96 (0.00)
CRATIO	-	0.19 (0.00)	0.10 (0.03)	0.19 (0.00)	0.11 (0.02)
LEV	+	1.83 (0.00)	1.43 (0.00)	1.89 (0.00)	1.47 (0.00)
LOGNUMAN	-	-0.24 (0.00)	-0.14 (0.01)	-0.24 (0.00)	-0.14 (0.02)
LOGSIZE	-	-0.27 (0.00)	-0.17 (0.00)	-0.27 (0.00)	-0.17 (0.00)
ROA	-	-3.75 (0.00)	-2.60 (0.00)	-3.72 (0.00)	-2.63 (0.00)
SDCFO	+	4.31 (0.00)	3.16 (0.00)	5.51 (0.00)	3.69 (0.00)
TANGIBLE	-	0.54 (0.02)	0.52 (0.00)	0.47 (0.04)	0.49 (0.00)
Year and Industry Dummies		Yes	Yes	Yes	Yes
N		1,256	1,256	1,255	1,255
Adjusted R-square		66.94%	77.08%	67.06%	77.22%

Table 4 reports the estimation results of the cost of debt regressions with two-sided  $p$  values (based on cluster corrected standard errors) reported in parentheses below the coefficients. The sample contains 1,310 firm-year observations from the year 1995 to 2007. To reduce the effect of outliers and keep the samples constant for comparison, we delete observations with absolute studentized residuals greater than two in all regressions. This outlier control technique causes slightly different numbers of observations for different model. The dependent variable is the cost of debt *YIELD\_SPREAD*. Accrual quality is proxied by *FLOS* in Model 1 and 2, and *ADJFLOS* in Model 3 and 4. Liquidity measures are not included in Model 1 and 3 but included in Model 2 and 4. The absolute difference between the coefficients of *FLOS* or *ADJFLOS* without and with liquidity measures is reported in the row *DIFF*, with the  $p$  value given below.

**Table 5**

**Controlling for Information Asymmetry Using PIN**

**Panel A. Accrual quality and Bond Liquidity, controlling for PIN**

$$LIQUIDITY_{j,t} = \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times PIN_{j,t} + \beta_3 \times LOGAGE_{j,t} + \beta_4 \times LOGMATURITY_{j,t} + \beta_5 \times LOGOFFER_{j,t} + \beta_6 \times BM_{j,t} + \beta_7 \times LEV_{j,t} + \beta_8 \times LOGNUMAN_{j,t} + \beta_9 \times LOGSIZE_{j,t} + \beta_{10} \times ROA_{j,t} + \beta_{11} \times SDCFO_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t}$$

Variable	Predicted sign	FLOS		ADJFLOS	
		Model1	Model2	Model3	Model4
		%NON_ZERO	NEG_BIDASK	%NON_ZERO	NEG_BIDASK
AQ	+	2.68 (0.00) [0.56]	1.27 (0.01) [0.62]	2.77 (0.00) [0.10]	1.92 (0.00) [0.23]
PIN	-	-0.28 (0.01)	-0.13 (0.08)	-0.30 (0.01)	-0.16 (0.04)
Other control variables, year and industry dummies		Yes	Yes	Yes	Yes
N		1,103	1,151	1,103	1,153
Adjusted R-square		60.55%	32.44%	60.35%	32.66%

**Panel B. Accrual quality and the Cost of Debt, controlling for PIN**

$$YIELD\_SPREAD_{j,t} = \beta_0 + \beta_1 \times AQ_{j,t} + \beta_2 \times \%NON\_ZERO_{j,t} + \beta_3 \times NEG\_BIDASK_{j,t} + \beta_4 \times PIN_{j,t} + \beta_5 \times LOGAGE_{j,t} + \beta_6 \times LOGMATURITY_{j,t} + \beta_7 \times LOGOFFER_{j,t} + \beta_8 \times BM_{j,t} + \beta_9 \times CRATIO_{j,t} + \beta_{10} \times LEV_{j,t} + \beta_{11} \times LOGNUMAN_{j,t} + \beta_{12} \times LOGSIZE_{j,t} + \beta_{13} \times ROA_{j,t} + \beta_{14} \times SDCFO_{j,t} + \beta_{15} \times TANGIBLE_{j,t} + YearDummies + IndustryDummies + \varepsilon_{j,t}$$

Variable	Predicted sign	FLOS		ADJFLOS	
		Model1	Model2	Model3	Model4
		W/O LIQ	W LIQ	W/O LIQ	W LIQ
AQ	-	-5.60 (0.03) [0.59]	-2.82 (0.17) [0.51]	-6.57 (0.03) [0.35]	-3.43 (0.18) [0.55]
DIFF			-2.78 (0.05) [0.40]		-3.14 (0.05) [0.09]
%NON_ZERO	-		-1.36 (0.00) [0.46]		-1.33 (0.00) [0.56]
NEG_BIDASK	-		-0.56 (0.00) [0.74]		-0.54 (0.00) [0.69]
PIN	+	0.26 (0.41)	-0.22 (0.42)	0.31 (0.32)	-0.16 (0.54)
Other control variables, year and industry dummies		Yes	Yes	Yes	Yes
N		1,132	1,132	1,132	1,132
Adjusted R-square		66.76%	76.59%	67.02%	76.49%

Table 5 presents the summary results of the liquidity regressions and cost of debt regressions after controlling for the effect of information asymmetry measured by the probability of informed trading (*PIN*), with two-sided *p* values (based on cluster corrected standard errors) reported in parentheses below the coefficients. For brevity we only report coefficients on *AQ*, *PIN*, and the two liquidity measures. The sample contains 1,182 firm-year observations from the year 1995 to 2007. The sample is slightly smaller than the one used in the primary analysis because of the missing *PIN* measure. To reduce the effect of outliers and keep the samples constant for comparison, we delete observations with absolute studentized residuals greater than two in either regression. See Table 1 for variable definitions.

Panel A Table 5 reports the coefficients of *AQ* and *PIN* in the liquidity regressions and their *p* values in round brackets below the coefficients. Liquidity is proxied by *%NON\_ZERO* in Model 1 and 3, and *NEG\_BIDASK* in Model 2 and 4. Accrual quality is proxied by *FLOS* in Model 1 and 2, and *ADJFLOS* in Model 3 and 4. The *p* values of the differences between the coefficients of *FLOS* and *ADJFLOS* before controlling for *PIN* (as in Table 3) and after controlling for *PIN* (as in Table 5, Panel A) are reported in square brackets.

Panel B Table 5 reports the coefficients of *AQ*, liquidity measures, and *PIN* in the cost of debt regressions and their *p* values in round brackets. The dependent variable is the *YIELD\_SPREAD*. Accrual quality is proxied by *FLOS* in Model 1 and 2, and *ADJFLOS* in model 3 and 4. The *p* values of the differences between the coefficients of *FLOS* and *ADJFLOS* before controlling for *PIN* (as in Table 4) and after controlling for *PIN* (as in Table 5, Panel B) are reported in square brackets. Liquidity measures are not included in Model 1 and 3 but included in Model 2 and 4. The *p* values of the differences between the coefficients of *%NON\_ZERO* and *NEG\_BIDASK* before controlling for *PIN* (as in Table 4) and after controlling for *PIN* (as in Table 5, Panel B) are reported in square brackets. The difference between the coefficients of *FLOS* and *ADJFLOS* without and with liquidity measures is reported in the row *DIFF*, with the *p* value given below in round brackets. The *p* values of the absolute differences between *DIFF* before controlling for *PIN* (as in Table 4) and *DIFF* after controlling for *PIN* (as in Table 5, Panel B) are reported in square brackets.



**Table 6**  
**Credit Ratings, Accrual quality, Liquidity, and Cost of Debt**

Model	<i>LOGRATING</i>				<i>COD</i>			
	<i>FLOS</i>		<i>ADJFLOS</i>		<i>FLOS</i>		<i>ADJFLOS</i>	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Variable	W/O	W LIQ	W/O	W LIQ	W/O	W LIQ	W/O	W LIQ
Intercept	1.38 (0.00)	1.37 (0.00)	1.35 (0.00)	1.36 (0.00)	7.79 (0.00)	6.42 (0.00)	7.80 (0.00)	6.38 (0.00)
<i>AQ</i>	0.71 (0.02)	0.34 (0.17)	0.83 (0.02)	0.37 (0.20)	-4.48 (0.02) [0.12]	-2.68 (0.11) [0.61]	-4.94 (0.04) [0.40]	-3.20 (0.15) [0.99]
<i>DIFF</i>		-0.37 (0.01)		-0.46 (0.00)		-1.80 (0.05) [0.02]		-1.74 (0.06) [0.13]
<i>%NON_ZERO</i>		0.13 (0.00)		0.13 (0.00)		-1.07 (0.00) [0.00]		-1.07 (0.00) [0.00]
<i>NEG_BIDASK</i>		0.09 (0.00)		0.10 (0.00)		-0.29 (0.00) [0.16]		-0.29 (0.00) [0.16]
<i>LOGAGE</i>	-0.03 (0.01)	-0.01 (0.07)	-0.02 (0.01)	-0.01 (0.08)	0.14 (0.01)	0.10 (0.03)	0.14 (0.01)	0.11 (0.03)
<i>LOGMATURITY</i>	0.03 (0.02)	0.03 (0.02)	0.04 (0.01)	0.03 (0.02)	0.18 (0.01)	0.21 (0.00)	0.18 (0.02)	0.21 (0.00)
<i>LOGOFFER</i>	-0.01 (0.04)	-0.01 (0.04)	-0.01 (0.04)	-0.01 (0.04)	-0.08 (0.05)	-0.08 (0.01)	-0.07 (0.07)	-0.07 (0.02)
<i>LOGRATING</i>					-3.66 (0.00)	-2.53 (0.00)	-3.61 (0.00)	-2.49 (0.00)
<i>BM</i>	-0.11 (0.00)	-0.10 (0.00)	-0.12 (0.00)	-0.10 (0.00)	0.58 (0.00)	0.62 (0.00)	0.62 (0.00)	0.66 (0.00)
<i>CRATIO</i>	-0.01 (0.21)	0.00 (0.79)	-0.01 (0.19)	0.00 (0.79)	0.14 (0.00)	0.10 (0.02)	0.15 (0.00)	0.10 (0.01)
<i>LEV</i>	-0.23 (0.00)	-0.18 (0.00)	-0.24 (0.00)	-0.18 (0.00)	0.98 (0.00)	0.97 (0.00)	1.02 (0.00)	1.01 (0.00)
<i>LOGNUMAN</i>	0.02 (0.07)	0.01 (0.46)	0.02 (0.05)	0.01 (0.40)	-0.19 (0.00)	-0.13 (0.00)	-0.20 (0.00)	-0.14 (0.00)
<i>LOGSIZE</i>	0.07 (0.00)	0.06 (0.00)	0.07 (0.00)	0.06 (0.00)	-0.04 (0.35)	-0.03 (0.31)	-0.04 (0.32)	-0.04 (0.26)
<i>ROA</i>	0.55 (0.00)	0.42 (0.00)	0.53 (0.00)	0.41 (0.00)	-1.44 (0.00)	-1.42 (0.00)	-1.32 (0.00)	-1.34 (0.00)
<i>SDCFO</i>	-0.73 (0.00)	-0.63 (0.00)	-0.88 (0.00)	-0.70 (0.00)	0.90 (0.06)	0.84 (0.05)	2.37 (0.01)	1.83 (0.02)
<i>TANGIBLE</i>	-0.06 (0.08)	-0.05 (0.08)	-0.04 (0.22)	-0.04 (0.16)	0.42 (0.02)	0.44 (0.00)	0.36 (0.05)	0.40 (0.01)
Year and Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,217	1,217	1,220	1,220	1,264	1,264	1,264	1,264
Adjusted R-square	75.23%	80.34%	75.04%	80.3%	75.21%	79.96%	75.21%	79.93%

Table 6 reports the results of the analyses on the complex relations among credit ratings, accrual quality, liquidity, and the cost of debt. Two-sided  $p$  values (based on cluster corrected standard errors) are reported in round brackets below the coefficients. The sample contains 1,310 firm-year observations from the year 1995 to 2007. To reduce the effect of outliers and keep the samples constant for comparison, we delete observations with absolute studentized residuals greater than two in either regression. See Table 1 for variable definitions.

The dependent variable in Model 1 to 4 is the natural logarithm of credit ratings. Accrual quality is proxied by *FLOS* in Model 1 and 2, and *ADJFLOS* in model 3 and 4. Liquidity measures are not included in model 1 and 3 but included in Model 2 and 4. The absolute difference between the coefficients of *FLOS* or *ADJFLOS* without and with liquidity measures is reported in the row *DIFF*, with the  $p$  value given below.

The dependent variable in Model 5 to 8 is *YIELD\_SPREAD*. These models differ from model 1-4 in Table 4 by including *LOGRATING* as an explanatory variable. Accrual quality is proxied by *FLOS* in Model 5 and 6, and *ADJFLOS* in model 7 and 8. The  $p$  values of the differences between the coefficients of *FLOS* and *ADJFLOS* before controlling for *LOGRATING* (as in Table 4) and after controlling for *LOGRATING* (as in Table 6) are reported in square brackets. Liquidity measures are not included in model 5 and 7 but included in Model 6 and 8. The  $p$  values of the differences between the coefficients of *%NON\_ZERO* and *NEG\_BIDASK* before controlling for *LOGRATING* (as in Table 4) and after controlling for *LOGRATING* (as in Table 6) are reported in square brackets. The difference between the coefficients of *FLOS* or *ADJFLOS* without and with liquidity measures is reported in the row *DIFF*, with the  $p$  value given below in round brackets. *DIFF* in both *LOGRATING* and *YIELD\_SPREAD* models shows the reduction in the coefficient of *AQ* after including liquidity measures. The  $p$  values of the differences between *DIFF* before controlling for *PIN* (as in Table 4) and *DIFF* after controlling for *PIN* (as in Table 6) are reported in square brackets.