ACCOUNTING QUALITY, BOND LIQUIDITY, AND THE COST OF DEBT

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March 2010

Preliminary Draft—Please Do Not Cite

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Acknowledgments: The paper has benefited greatly from helpful comments by Joseph Weber and Mohan Venkatachalam.
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Abstract

This paper investigates the role of accounting quality in improving bond liquidity and its implication on the cost of debt. We argue that high accounting quality not only reduces information asymmetry, but also decreases overall uncertainty in the market, thereby improving liquidity. We first document that higher accounting quality is associated with higher bond liquidity. We then show that the previously documented effect of accounting quality in reducing the cost of debt is largely through the improved liquidity. This is the first paper that examines the role of accounting quality in the bond market, and our results highlight the importance of information quality in improving liquidity.

Keywords: accounting quality, bond liquidity, cost of debt
1. Introduction

During the recent financial crisis, uncertainty about the value of mortgage securities caused liquidity to dry up and prices to crash in the debt markets. This triggered a financial contagion that spread to other markets, threatening to destroy the world’s financial structure and plunging economies into a severe slump that they are still struggling to overcome (see, for example, 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 and information quality is crucial to maintaining liquidity. Therefore, it is important to study the effect of accounting (information) quality on debt market liquidity and the implications of this effect on the cost of debt. The extant literature, however, has focused primarily on studying the effect of accounting quality on the cost of equity capital, from the angle of whether “information risk” is a non-diversifiable factor that is priced by the stock market (e.g., Francis et al., 2005; Core et al., 2008; Hughes et al., 2009). In contrast, in this paper we investigate (1) the association between accounting quality and bond liquidity; and (2) whether the association between accounting quality and bond liquidity explains the established association between accounting quality and the cost of debt (Francis et al., 2005).

We begin by hypothesizing that accounting quality improves bond liquidity for two reasons. First, high quality information lowers information asymmetry between informed and uninformed traders, which improves liquidity by reducing bid-ask spreads and increasing depth (Kyle, 1985). Second, high quality information increases the overall informedness in the market, which improves liquidity by reducing uncertainty about asset values and facilitating informed
trading. In addition, in the bond market, lowered uncertainty reduces the market maker’s inventory and search costs, which leads to further improvement in liquidity.

Next, we extend the hypothesized relation between accounting quality and bond liquidity to propose that accounting quality could indirectly affect the cost of debt through its effect on liquidity. We base our prediction on the large literature that documents that liquidity lowers expected returns (e.g., Amihud, 1986) and in particular that higher liquidity is associated with lower cost of debt (Chen et al., 2005). Prior literature has documented a relation between accounting quality and cost of debt, arguably through information risk (Francis et al., 2005). Therefore, this triangular relation between accounting quality, liquidity and cost of debt raises several interesting questions such as: (1) whether liquidity is an additional path through which accounting quality affects the cost of debt; (2) whether there exists a direct relation between accounting quality and the cost of debt after controlling for the liquidity path; and (3) if both paths exist, which one dominates the other.

We note that prior research has examined whether earnings quality can affect cost of capital through its effect on information asymmetry (e.g., Easley et al., 2002, 2004). Information asymmetry is often measured using bid-ask spreads or its components such as PIN (Easley et al., 2002; Bhattacharya et al., 2009b). In this paper, however, we examine liquidity as a distinct economic construct rather than as a proxy for information asymmetry. First, note that liquidity has a broader connotation than information asymmetry. For example, liquidity cost has components other than information asymmetry that could also be affected by earnings quality, such as inventory cost and search cost. Second, while it is uncontroversial that liquidity is priced (Amihud et al., 2005; Chen et al., 2005), whether information risk is priced is still open to debate (Hughes et al., 2005; Lambert et al., 2007; Mohanram and Rajgopal, 2009). In particular, Duarte
and Young (2008) report that the PIN component related to asymmetric information is not priced, while the PIN component related to illiquidity is priced.

We test our predictions on a sample of 2,105 firm-year observations over the period from 1995 to 2008. Following Chen et al. (2007), we measure bond liquidity using weighted average percentage of non-zero returns and bid-ask spreads.¹ Consistent with prior research, our measures of accounting quality are the accrual quality measures proposed by Dechow and Dichev (2002) (henceforth, the $DD$ measure), and Francis et al. (2005) (henceforth, the $FLOS$ measure). To alleviate the concern that our accrual quality measures merely capture the effects of operating volatility (Liu and Wysocki, 2007), we also use an adjusted $FLOS$ measure (henceforth the $ADJFLOS$ measure) that is orthogonal to operating volatility. Finally, we measure the cost of debt using weighted average yield spreads, which is the yield of a corporate bond minus the yield of a maturity matched Treasury bond.

We begin our analysis by separately regressing the two bond liquidity measures on the three accrual quality measures. In all regressions, we control for both 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 of accrual quality in each of our six regressions. This effect is economically significant. For example, moving from the 5th to the 95th percentile of accrual quality results in an average increase of 6% to 10% in the number of non-zero trading days and a 11% to 18% reduction in bid-ask spreads. Overall, we document that accounting quality does have a significant positive effect on bond liquidity.

¹ 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. We multiply bid-ask spreads by -1 so that larger values of the liquidity measure represent higher levels of liquidity.
We next examine the triangular association between accounting quality, bond liquidity, and the cost of debt. After controlling for both bond and firm characteristics, we find a negative association between the cost of debt and accounting quality, which is consistent with findings in prior studies (e.g. Francis et al., 2005). The magnitude of the coefficient of accounting quality, however, either drops significantly or becomes insignificant when we control for bond liquidity. Path analysis reveals that earnings quality has both a direct effect on the cost of debt and an indirect effect through liquidity, and the direct and indirect effects are comparable in magnitudes. An analysis of incremental explanatory power, however, suggests that the explanatory power of accounting quality for cost of debt arises primarily through its effect on liquidity; when using either the $FLOS$ or $ADJFLOS$ proxies, accounting quality has zero incremental explanatory power after accounting for the explanatory power arising through liquidity. Overall, our results suggest that the effect of accounting quality in reducing the cost of debt arises largely through its effect on bond liquidity.

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 accounting quality in improving bond liquidity. Recent working papers (Bhattacharya et al., 2009a; Ng, 2009) examine the association between accounting quality and liquidity (or liquidity risk) in the stock market. It is important to understand the role of accounting 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 features in the over-the-counter bond market provides a powerful setting to detect the impact of accounting 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 accounting quality (e.g., Easley et al., 2002, 2004; Bhattacharya et al.,
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. Therefore, it is important to examine the effect of
accounting (information) quality on liquidity in general, rather than merely its asymmetric
information component. Finally, we provide insights into how accounting quality affects the cost
of debt through its effect on bond liquidity. While theory suggests that earnings quality can affect
the cost of capital either directly or indirectly through reducing information asymmetry or
improving liquidity, we are the first to test the liquidity explanation. We show that accounting
quality’s effect on cost of debt arises largely through the liquidity path.

The remainder of the paper is organized as follows. The next section discusses the
literature and motivates our analyses. Section 3 describes our sample and empirical proxies.
Section 4 presents the analysis on the link between earnings quality and bond liquidity. Section 5
presents the analysis on the link between earnings quality, bond liquidity, and the cost of debt. In
Section 6 we report the results of robustness check. Section 7 summarizes our findings and
concludes.

2. Motivation

2.1 The importance of studying accounting quality and bond liquidity

The U.S. corporate bond market is enormous. For example, in 2008, the principal value
of outstanding corporate bonds was $6.2 trillion. Bonds are the primary source of external
financing for U.S. corporations and are far bigger than equity. 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. Thus the importance of the corporate bond market for the business sector and even the entire economy cannot be overemphasized.

Liquidity is vital to the health of the debt markets. For example, during the recent financial crisis, liquidity dried up in the subprime mortgage market and illiquidity spread rapidly to markets with little connection to the mortgage market. The loss of liquidity resulted in a financial panic and a “flight to quality” by investors, who moved their investments to the least risky assets such as Treasury securities. The resulting financial contagion crashed asset prices in several markets and precipitated a severe credit crunch where even the most creditworthy borrowers were unable to borrow at reasonable rates and terms. The credit crunch ultimately 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).

What caused this liquidity crisis? Among several factors that have been identified, one key factor is the uncertainty about asset values (Getter et al., 2007). For example, Krishnamurthy (2009) concludes that investors’ response to uncertainty is to disengage from risks and seek liquid investments, which can lead to a liquidity crisis dynamic. Also, in the words of an economist from Moody’s, “…a big problem is that lenders don’t know which of their clients is likely to default because the system is so opaque, so they stop lending to everybody” (Tully, 2007, p. 50). This is consistent with theories suggesting that uncertainty and information asymmetry can lead to illiquidity and market failure (e.g., Akerlof, 1970). These viewpoints underscore the crucial role that information quality may play in fostering liquidity and thus maintaining the health of debt markets.

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2 Source: Securities Industry and Financial Markets Association (www.sifma.org)
Thus far, we have discussed the importance of the debt markets to the economy and the importance of high quality information in helping provide liquidity to the debt markets. Despite the importance of this topic, we are unaware of academic research that investigates the role of information quality in improving debt market liquidity. In this paper, we fill this void by examining whether higher accounting quality is associated with higher bond liquidity and whether this association explains the negative relation between accounting quality and cost of debt.

2.2 The relation between accounting 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. Even under normal circumstances, in specialist markets (such as the bond market) the 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.

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 bond markets), high quality public information reduces information asymmetry by lowering the value of the private information gathered 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
hypothesize that higher accounting quality improves liquidity in the bond market through reduced 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 (Krishnamurthy, 2009b). 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”.\(^3\) Intuitively, when traders are uncertain (i.e., less informed) about a security’s value they cannot agree on a price. Consequently, they are less willing to trade, thereby reducing liquidity and leading to deleterious consequences, including plummeting prices.

In addition to this effect, in specialist markets—such as the bond market—reduced uncertainty can further improve liquidity through lower 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). Better informed specialists are less subject to inventory risk from price changes and therefore their inventory costs are lower. Also, in the bond markets, which are typically less liquid and more dominated by large traders than the stock market, specialists also incur search costs to locate counterparties and induce them to trade through price discounts. It is easier to locate counterparties when

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\(^3\) 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.”
traders are generally better informed because traders are more willing to trade with better information. Therefore, better information reduces search frictions and allows specialists to more easily adjust order imbalances without changing prices. To summarize, superior information reduces both inventory and search costs incurred by specialists, who in turn decrease bid-ask spreads and increase depth, thereby improving liquidity.

In summary, we hypothesize that higher accounting quality improves liquidity in the bond markets. The improvement in liquidity is predicted to arise because better public information can both reduce information asymmetry and improve the average informedness of traders, that is, reduce uncertainty. As discussed earlier, a reduction in both information asymmetry and uncertainty improves liquidity in the bond market.

Two concurrent working papers examine the association between accounting quality and liquidity related variables in the stock market. Bhattacharya et al. (2009a) 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. Specifically, he 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 accounting quality on liquidity in the stock market, we study how accounting quality affects liquidity in the bond market for several reasons. First, we note in section 2.1 that the bond market is much larger and arguably more 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., 2005). The third reason to study bond liquidity is that the bond market has several unique features that make liquidity more important for bonds than for stocks. Finally, illiquidity is a more widespread phenomenon in the bond market. In contrast, stocks other than for the tiniest companies are fairly liquid (Nallareddy and Subramanyam, 2010). Figure 1 illustrates this point by examining the distribution of the percentage of non-trading days (zero returns) by firm size for a large cross-section of stocks and bonds. First, the number of non-trading (zero return) 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, this suggests that bond illiquidity is a more widespread phenomenon than stock illiquidity.

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

Classic asset pricing models assume that information issues are irrelevant because they can be diversified away. This assumption has been questioned recently by a burgeoning literature on information risk that 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 two different paths by which information

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4 Bonds are traded over the counter with a few market makers; therefore, liquidity costs are amplified in the bond market. For example, because there is no centralized market and investors trade bilaterally, the inventory cost and search cost are higher for the bond market maker than for the stock exchanges. Also, the information asymmetry cost is larger in the bond market since bonds are mostly held by institutional investors who are considered more informed. In addition, the opaqueness of over the counter market adds to the lack of information on order flow. 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).

5 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.
quality is priced in a firm’s cost of capital. The first path is through information asymmetry. Easley and O’Hara (2004) propose a model wherein information asymmetry arising from poor information quality is a non-diversifiable risk that is directly reflected in the firm’s expected return. Earlier papers such as Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) theorize an indirect link between information asymmetry (arising from public information quality) and the cost of capital through the information asymmetry component of the firm’s bid-ask spreads. In contrast to the information asymmetry path, Lambert et al. (2007) propose that earnings quality can directly affect the cost of equity capital because earnings quality reduces the firm’s non-diversifiable covariances with other firms’ cash flows. Empirically, Francis et al. (2005) find that poorer accounting quality is associated with higher implied cost of equity. Easley et al. (2002) find that PIN (a proxy for information asymmetry) is associated with realized returns. A recent working paper (Bhattacharya et al., 2009b) finds that the association between accounting quality and the implied cost of equity arises through both a direct path from earnings quality to the cost of equity and an indirect path through information asymmetry (proxied by the adverse selection component of bid-ask spreads and PIN).

However, the link of information quality to the cost of capital 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 accounting quality is not a priced risk factor, that is, it has no association with future returns. Also, Mohanram and Rajgopal (2009) cast doubts on whether the information asymmetry (proxied by
PIN) reflects information risk that is systematically priced by investors. Finally, Duarte and Young (2008) show that the information asymmetry component of PIN is not priced by the market, but the illiquidity component is priced.

In this paper, we explore a third path through which accounting quality may affect the cost of capital: indirectly through its effect on liquidity. In Section 2.2 we hypothesize that accounting quality is positively associated with liquidity. Moreover, 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 an accepted priced risk factor, we hypothesize that accounting quality affects the cost of capital through its effect on liquidity. The advantage of this link is that it is not subject to concerns of whether accounting (information) quality is a non-diversifiable priced risk factor. As long as accounting quality affects liquidity, it is expected to affect the cost of capital because liquidity has a well accepted relation to the cost of capital.

We acknowledge that the link between information quality and the cost of capital through its effect on liquidity has been proposed in the context of information asymmetry (e.g., Diamond and Verrecchia, 1991; Kim and Verrecchia, 1994). Liquidity measures (such as bid-ask spreads) have also been used as proxies for information asymmetry (Bhattacharya, et al., 2009a, b). However, as noted in Section 2.2, the liquidity cost has components unrelated to information asymmetry, such as the transaction cost, inventory cost, and search cost. This is particularly true in the bond market where the inventory cost and search cost are more significant than that in the stock market. Moreover, whether information risk from information asymmetry is priced is still
controversial. Consistent with this notion, Duarte and Young (2008) report that the PIN component related to asymmetric information is not priced, while the PIN component related to illiquidity is priced. In this context it is important to note that we study liquidity as a distinct economic construct and not merely as an embodiment of information asymmetry.

In the context of the stock market, Ng (2009) examines whether liquidity risk subsumes much of the cost-of-capital effects of information quality. Our focus, however, is the bond market. In addition, we study liquidity as opposed to the information asymmetry component. We propose that accounting quality improves bond liquidity. Prior research has provided evidence that both accounting quality and bond liquidity are associated with lower cost of debt (Francis et al., 2005; Chen et al., 2005). These potentially constitute a triangular relation among accounting quality, bond liquidity, and the cost of debt. We test this relation by examining whether liquidity is a possible channel through which accounting quality may affect the cost of debt. And if so, we examine whether the dominating effect on the cost of debt is the direct effect of accounting quality or the indirect effect of accounting quality through liquidity.

3. Sample, variables, and descriptive data

3.1. Sample selection

Table 1 summarizes our sample selection process. We start from the Thomson Reuters Datastream database and collect daily price and yield spread data for 2,125 firms from 1993 to 2009. We then merge the Datastream data with the Mergent Fixed Income Securities Database (FISD) to obtain bond characteristics, such as issuing amount, maturity, and S&P credit rating. This step excludes 52 firms. We further merge the data with Compustat to acquire firm characteristics. We have 1,104 firms left after merging with Compustat.
We manually collect quarterly bid and ask prices from the Bloomberg Terminal, which are available for 499 firms. The loss of observations from merging with Bloomberg is significant but not unusual. For example, Chen et al. (2007) 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.6 We eliminate observations with missing S&P ratings in FISD, or negative spreads in Datastream. As in Francis et al. (2005), we exclude all firm-years with negative total assets, book value and market value of equity. These sample screenings reduce our sample to 2,292 firm-years representing 424 distinct firms.

To preserve our sample from unnecessary cuts, we let our final sample vary with the availability of time series data required to calculate the accounting quality (AQ) measures, $DD$, $FLOS$, and $ADJFLOS$ (see below for a detailed description of these measures). Table 1 reports the number of observations in the $DD$, $FLOS$, and $ADJFLOS$ samples. We note that the actual numbers of observations in our regression models are slightly lower than those reported in Table 1 because of the application of outlier control techniques. Specifically, in all our regressions, we delete observations with absolute standardized residuals greater than two (Belsley et al. 1980).

3.2. Proxies and variable definitions

3.2.1. Accounting quality measures

Table 2 provides the definitions of all variables used in the analyses. We use three alternative accounting quality measures based on Dechow and Dichev (2002) and Francis et al. (2005). For the ease of interpretation, we multiply all three measures by -1 so that higher values of AQ measures represent better accounting quality.

In order to ensure that the loss of observations from Bloomberg does not create significant sample biases, we examine various sample characteristics between the initial Datastream sample and the Bloomberg sample. Untabulated results indicate that the Bloomberg sample tends to have larger market value and total assets; but other than the bias toward larger firms, we do not find any other significant difference.
The first accounting quality measure, $DD$, is the Dechow and Dichev (2002) accrual quality. We estimate the following regression for each firm:

$$\frac{TCA_{jt}}{Assets_{jt}} = \alpha_0 + \alpha_1 \frac{CFO_{jt}}{Assets_{jt}} + \alpha_2 \frac{CFO_{jt}}{Assets_{jt}} + \alpha_3 \frac{CFO_{jt}}{Assets_{jt}} + \alpha_4 \Delta Rev_{jt} + \alpha_5 \frac{PPE_{jt}}{Assets_{jt}} + v_{jt},$$

where $TCA_{jt}$ is firm j’s total current accrual, computed as $\Delta CA_{jt} - \Delta CL_{jt} - \Delta Cash_{jt} + \Delta STDEBT_{jt}$, $Assets_{jt}$ is firm j’s average total assets in year t, $CFO_{jt}$ is firm j’s cash flow from operations in year t, computed as $NI_{jt} - TA_{jt}$, where $NI_{jt}$ is firm j’s net income before extraordinary items (IB in Compustat), $TA_{jt} = \Delta CA_{jt} - \Delta CL_{jt} - \Delta Cash_{jt} + \Delta STDEBT_{jt} - Depre_{jt}$. $ACA_{jt}$ is firm j’s change in current assets (ACT in Compustat), $\Delta CL_{jt}$ is firm j’s change in current liabilities (LCT in Compustat), $\Delta Cash_{jt}$ is firm j’s change in cash (CHE in Compustat), $\Delta STDEBT_{jt}$ is firm j’s change in debt in current liabilities (DLC in Compustat), and $Depre_{jt}$ is firm j’s depreciation and amortization expenses (DP in Compustat). We take the rolling standard deviation of firm j’s residuals over year t-6 through t as our first accounting quality measure.7

The second earnings quality measure, $FLOS$, is the modified Dechow and Dichev measure as in Francis et al. (2005). We estimate the following regression for each of Fama and French’s (1997) 48 industry groups in year t:8

$$\frac{TCA_{jt}}{Assets_{jt}} = \alpha_0 + \alpha_1 \frac{CFO_{jt}}{Assets_{jt}} + \alpha_2 \frac{CFO_{jt}}{Assets_{jt}} + \alpha_3 \frac{CFO_{jt}}{Assets_{jt}} + \alpha_4 \Delta Rev_{jt} + \alpha_5 \frac{PPE_{jt}}{Assets_{jt}} + v_{jt},$$

where $\Delta Rev_{jt}$ is firm j’s change in revenues (SALE in compustat), and $PPE_{jt}$ is firm j’s gross value of property, plant, and equipment (PPEGT in compustat) (all other variables follow the definitions in the previous paragraph). We take the rolling standard deviation of firm j’s residuals over year t-6 through t as our second accounting quality measure.

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7 We choose seven years to allow a long enough time series for the standard deviation, but not too long to impose unnecessary sample cut. Our results are robust to different lengths of the rolling window.

8 Following Francis et al. (2005), we winsorize the input variables at 1% and 99% of the distribution.
To alleviate the concern that FLOS captures operating volatilities, we include a third earnings quality measure ADJFLOS, which is the residual from the following regression:

\[ FLOS_{jt} = \alpha_0 + \alpha_1 SDACCR_{jt} + v_{jt} \]

where FLOS\(_{jt}\) is firm j’s FLOS measure in year t, and SDACCR\(_{jt}\) is the rolling standard deviation of firm j’s current accruals over years t-6 through t.

### 3.2.2. Bond liquidity measures

Following Chen et al. (2007), we use two direct bond liquidity measures, the percentage of non-zero bond returns, and negative 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 weights.

Our first liquidity measure is derived from the daily bond prices from Datastream. The incidence of no price changes, that is, zero bond returns, suggests lack of trading activities and thus illiquidity. Since higher percentage of zero return indicates less liquidity, we use percentage of non-zero return 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.

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

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9 Direct bond liquidity measures based on transaction data were historically difficult to obtain because of limited data availability; therefore, many empirical papers use indirect measures as liquidity proxies such as bond age, issuing amount, whether the bond is on-the-run, the number of active traders, yield dispersion, or yield volatility (Houwelling et al., 2005).

10 All bond level variables are aggregated into firm level using offering amount as the weight except the offering amount itself, which is aggregated by taking the sum.

11 We use clean prices because gross prices include accrued interests that mechanically introduce price changes for every day.
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. Since larger bid-ask spreads represent less liquidity, we multiply bid-ask spreads by -1 to get the second liquidity measure \textit{NEG\_BIDASK} so that larger values of \textit{NEG\_BIDASK} correspond to higher levels of liquidity.

\textbf{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.\footnote{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.} 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, \textit{YIELD\_SPREAD}, expressed in percentages.

\textbf{3.2.4. Control variables}

We control for three bond characteristics, age, maturity and offering amount.\footnote{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.} Bond age has been documented to have a negative effect on liquidity since an increasing percentage of the issue is subsumed in buy-and-hold portfolios as the bond ages, rendering the bond less liquid.
Bonds of larger offering amount tend to be owned and analyzed by more investors and consequently have lower information costs thus higher liquidity (Crabbe and Turner, 1995). Larger issues are also less likely to be locked in buy-and-hold portfolios and refrain from reduced tradable amount, 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 (BM), leverage (LEV), return on assets (ROA), current ratio (CRATIO), tangibility (TANGIBLE), and operating cash flow volatility (SDCFO). Bonds issued by firms with higher return on assets may trade with higher liquidity because of better firm performance. Larger firms and firms with higher number of analysts following may have higher bond liquidity because of better information environment. High operating cash flows volatility, high leverage, high book-to-market, low tangibility ratio, and low current ratio may signal financial and operating risk that posts potential threat to the bond value, resulting in lower liquidity. We note that another reason to control for operating cash flow volatility is that the accounting quality measure could simply capture operating volatility. We attempt to mitigate this concern by using an adjusted FLOS measure and also by controlling for the operating volatility explicitly.

3.3. Descriptive statistics

3.3.1. Statistical properties

Panel A of Table 3 reports descriptive statistics for the variables used in our analyses. Our sample firms have slightly higher accounting quality than reported in Dechow and Dichev (2002) and Francis et al. (2005), presumably because our sample consists of bond issuers that are
generally large and financially healthy. The mean (median) of our \( DD \) measure before multiplying by -1 is 0.012 (0.009) while Dechow and Dichev (2002) report a mean (median) of 0.028 (0.020). The mean (median) of our \( FLOS \) measure is 0.031 (0.026) while Francis et al. (2005) report a mean (median) of 0.044 (0.031).\(^{14}\)

In terms of the liquidity measures, the mean percentage non-zero return (%\textit{NON\_ZERO}) is 75%, which means on average our sample firms have no price movements in 25% of the trading days out of the fiscal year. It is comparable to the statistics in Chen et al. (2007), which report 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 94.8%, indicating that the distribution of this liquidity measure is negatively skewed and there are some highly illiquid bonds in the sample. The illiquidity of our sample bonds lends support to our motivation to study bond liquidity; that is, firms on average suffer from low bond liquidity and improving accounting quality could be more helpful in boosting bond liquidity than stock liquidity. The mean \( \text{NEG\_BIDASK} \) of our sample firms is -0.44%, representing an average bid-ask spread of 0.44%. Chen et al. (2007) report an average bid-ask spread of 0.58% for a different sample period. The mean (median) \( \text{YIELD\_SPREAD} \), our cost of debt measure, is 2.28% (1.68%). We express both \( \text{NEG\_BIDASK} \) and \( \text{YIELD\_SPREAD} \) in percentages instead of basis points for the ease of interpretation of the coefficients in the regressions. Not surprisingly, our sample firms are larger (median total assets are $6,860 million), more profitable (median return on assets is 0.09), and more highly leveraged (median leverage ratio is 0.48) than COMPUSTAT population because only large and financially healthy firms are able to issue large amounts of public debt.

3.3.2. Correlations

\(^{14}\) Note that high values of these measures before multiplying by -1 correspond to lower accounting quality.
Panel B presents the Pearson (above) and Spearman (below) correlations between variables. The two bond liquidity measures, \textit{\%NON ZERO} and \textit{NEG_BIDASK}, are significantly correlated with a Pearson (Spearman) correlation of 0.45 (0.35), lending support to the construct validity of the liquidity measures. The Pearson correlations between liquidity and accounting quality range from 0.13 (between \textit{FLOS} and \textit{NEG_BIDASK}) to 0.21 (between \textit{FLOS} and \textit{\%NON ZERO}). This is consistent with our hypothesis that accounting quality has a positive association with liquidity. The cost of debt is negatively associated with all three accounting quality measures, consistent with findings in prior studies that firms with better accounting quality have lower cost of capital (Francis et al., 2005). The Pearson correlation between \textit{\%NON ZERO} and \textit{YIELD_SPREAD} is -0.55 and that between \textit{NEG_BIDASK} and \textit{YIELD_SPREAD} is -0.42. 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 liquidity and the cost of debt are more than twice of the correlations between accounting quality and the cost of debt, suggesting that liquidity has a higher order of effect on the cost of debt than accounting quality. Lastly, the bond and firm characteristics are also significantly correlated with liquidity and the cost of debt in the expected direction, with the exception of tangibility ratio, which is largely uncorrelated with either liquidity or the cost of debt.

4. Accounting quality and bond liquidity

4.1. Modeling liquidity

We hypothesize that \textit{ceteris paribus}, firms with higher accounting quality have higher bond liquidity. We run the following regression to test this relation:
where Liquidity is either \%NON_ZERO or NEG_BIDASK. AQ is one of the three accounting quality measures, \textit{DD}, \textit{FLOS}, or \textit{ADJFLOS}. A positive coefficient on AQ (\(\beta_1\)) is consistent with our hypothesis that higher accounting quality is associated with higher bond liquidity. To control for the effects of outliers, we delete observations with absolute standardized residuals greater than two in all regressions.

We control for bond characteristics such as age (\textit{LOGAGE}), maturity (\textit{LOGMATURITY}), and offering amount (\textit{LOGOFFER}). Sarig and Warga (1989) show that as the bond ages, an increasing percentage of the issue is held in buy-and-hold portfolios and as a result the bond is less liquid. Bonds with larger offering amount attract more attention and analysis from investors and incur lower information costs to traders, which in turn facilitates bond trading and improve liquidity (Crabbe and Turner, 1995). Larger issues are also less likely to be locked in buy-and-hold portfolios, making large amount tradable and therefore are more liquid (Amihud and Mendelson, 1991). We also control for firm characteristics that proxy for risk and information environment. We expect a negative relation between liquidity and the standard deviation of operating cash flows (\textit{SDCFO}), book-to-market ratio (\textit{BM}), and leverage (\textit{LEV}) since riskier bonds have lower liquidity. We expect a positive relation between liquidity and return on assets (\textit{ROA}) because bonds issued by better performing firms are more attractive to bondholders. Firm size (\textit{SIZE}) and the number of analysts (\textit{NUMAN}) are indicators of the overall information environment that firms operate in. Better information environments and lower information costs are likely to increase market participants’ willingness to trade, resulting in better bond liquidity. All control variables are defined in Table 2.
4.2. Regression results

Table 4 reports the results of the liquidity regressions. Six models are generated from the combination of three accounting quality measures as the independent variable and two liquidity measures as the dependent variable. In all six regressions, we find positive and significant coefficients on accounting quality. When the dependent variable is the percentage of non-zero bond returns (%NON_ZERO), the coefficients of AQ on liquidity are 3.37 (DD in Model 1), 1.02 (FLOS in Model 2), 1.30 (ADJFLOS in Model 3), and are all significant at \( p < 0.01 \) level. The positive impact of accounting quality on liquidity is economically significant. When AQ measures move from 5% to 95% of its distribution, the average sample firm experiences a 6% (Model 2) to 10% (Model 1) reduction in the number of no trading days. In the bid-ask spread models, the coefficients of AQ on liquidity range from 1.02 in Model 5 (FLOS) to 2.80 in Model 4 (DD). An increase from 5% to 95% in the AQ measures results in a reduction of 0.05% (FLOS in Model 5) to 0.08% (DD in Model 4) in bid-ask spreads in absolute values. This translates into an 11% to 18% reduction in bid-ask spreads for the average firm in our sample. These results are consistent with our hypothesis that better accounting quality is associated with higher levels 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, decreasing with the percentage of trading days with no price changes but increasing with the bid ask spreads. This attests to the complex relationship between maturity structure and bond liquidity. Bond offering amount is negatively related to liquidity, contrary to our expectation, possibly because when firm size is present in the regression, the offering amount turns into a leverage measure. The firm characteristics appear to have the expected effects on bond liquidity. The book-to-market (BM) and leverage (LEV) are
negatively correlated with liquidity, confirming that higher risk leads to lower bond liquidity. Better firm performance (ROA) is associated with higher bond liquidity. The standard deviation of operating cash flows (SDCFO) has a negative effect on liquidity. The effects of accounting quality on liquidity are significant after controlling for operating volatility (SDCFO), alleviating the concern that accounting quality may simply capture operational volatility. The coefficients of the number of analysts following and firm size are significantly positive, consistent with that better general information environment facilitates trading and enhances liquidity.

5. Accounting quality and the cost of debt

5.1. Modeling the cost of debt

The next question we ask is whether better accounting quality is associated with lower cost of debt and more importantly, whether this association exists in the presence of bond liquidity. We use the following model to test the effect of accounting quality on the cost of debt:

\[
\text{YIELD\_SPREAD}_{ij} = \beta_{0j} + \beta_{1j} \times AQ_{ij} + \beta_{2j} \times \%\_NON\_ZERO_{ij} + \beta_{3j} \times \text{NEG\_BIDASK}_{ij} + \beta_{4j} \times \text{LOGAGE}_{ij} + \beta_{5j} \times \text{LOGMATURITY}_{ij} + \beta_{6j} \times \text{LOGOFFER}_{ij} + \beta_{7j} \times \text{BM}_{ij} + \beta_{8j} \times \text{CRATIO}_{ij} + \beta_{9j} \times \text{LEV}_{ij} + \beta_{10j} \times \text{LOGNUMAN}_{ij} + \beta_{11j} \times \text{LOGSIZE}_{ij} + \beta_{12j} \times \text{ROA}_{ij} + \beta_{13j} \times \text{SDCFO}_{ij} + \beta_{14j} \times \text{TANGIBLE}_{ij} + \text{YearDummies} + \text{IndustryDummies} + \epsilon_{ij},
\]

where all variables are as defined in Table 2.

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. As in our liquidity model, we control for three bond characteristics, bond age, bond maturity, and offering amount, and firm characteristics such as the standard deviation of operating cash flows, book-to-market ratio, leverage, return on assets, firm size, and the number of equity analysts covering the firm. Newly issued bonds are also likely to be underpriced so bond age is expected to be negatively associated with yields (Houwelling et al., 2005). However, bond age may be
positively associated with yield spread because older bonds are in general less liquid. 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 more volatile operating cash flows, larger book-to-market ratio, higher level of leverage, and lower return on assets since bondholders may perceive bonds issued by these firms as riskier and require higher premium. We predict 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, who in turn may ask for lower premium. In addition, following Bharath et al. (2008), we include the tangibility ratio \( TANGIBLE \) and current ratio \( CRATIO \) in the cost of debt model. Other things being equal, firms with more tangible assets and more current assets are less likely to default and therefore lower the cost of debt; therefore we expect both \( TANGIBLE \) and \( CRATIO \) to have negative coefficients.

5.2. Regression results

Table 5 presents the results for the cost of debt analysis. We report results for the yield spread models with and without liquidity measures to allow for the comparison of the coefficients on AQ with and without the effect of liquidity. Without liquidity measures, \( DD \), \( FLOS \), and \( ADJFLOS \) are significant and negative in explaining yield spreads (Model 1, 3, and 5). When we include both liquidity measures, however, the coefficients of the AQ measures are reduced considerably or even become insignificant. In particular, when the accounting quality is proxied by \( DD \), the coefficient of AQ reduces from -12.30 in Model 1 (without liquidity) to -8.19
in Model 2 (with liquidity). The difference is statistically significant at 0.10 and represents a difference of 12.3% in yield spreads when the value of $DD$ moves from 5% of the distribution to 95%. The reduction in the effects of AQ is even more profound in the cases of $FLOS$ and $ADJFLOS$, in which the coefficients of AQ become insignificantly different from zero or only marginally significant after including liquidity measures. While our results are consistent with prior studies that better accounting quality is associated with lower cost of debt, the comparison between models with and without liquidity measures suggests that the effect of accounting quality on the cost of debt is largely subsumed by bond liquidity.

Of the three bond characteristics, only bond age significantly affects the cost of debt in the expected direction in all six models. The coefficients of 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 almost always insignificant, 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 ($CRATIO$). As expected, higher book-to-market ratio ($BM$), leverage ($LEV$), and the standard deviation of operating cash flows ($SDCFO$), increase the cost of debt, while higher firm performance ($ROA$), size ($LOGSIZE$), and number of analysts ($LOGNUMAN$) decrease the cost of debt. Like AQ, the coefficients of firm controls appear to be larger in models without liquidity than those in models with liquidity. We expect $CRATIO$ to have a negative effect on the cost of debt since larger $CRATIO$ represents more liquid assets and higher ability of the firms to repay debts in the short
term. Table 5, however, reports positive coefficients of CRATIO. This may be caused by the high correlation between TANGIBLE and CRATIO.

5.3. Accounting quality and the cost of debt: the total, direct, and the indirect effect

Regression results suggest that the effect of accounting quality on the cost of debt reduces significantly or even disappears after bond liquidity is included to explain the cost of debt. In this section we directly test whether bond liquidity mediates the relation between accounting quality and the cost of debt. We hypothesize that accounting quality affects the cost of debt both directly and indirectly through liquidity. To formally test this hypothesis, we use path analysis and decomposition of the incremental explanatory power. Path analysis allows us to compare the magnitude of the direct effect of accounting quality on the cost of debt and the indirect effect through liquidity. The decomposition of the incremental explanatory power enables us to identify the explanatory power associated with the direct effect of accounting quality on the cost of debt and its indirect effect through liquidity.

5.3.1. Path analysis and structural equation models

Path analysis has been used in accounting studies and to a wider extent in the management accounting literature (see Shields, 1997 and Smith and Langfield-Smith, 2004 for a review). It is a statistical method for assessing and comparing the strengths of the direct and indirect relationships among variables (Lleras, 2005). It sets up a system of relationships that models multiple structural equations simultaneously and uses the fit of the correlation matrix to estimate the set of parameters in the structural equations (Wright, 1921, 1960).\(^\text{15}\) Notably, path analysis allows a variable to be a dependent variable in one relationship and an independent variable in another, which is referred to as a mediating or intervening variable. Path analysis

\(^{15}\) In such a system of relationships, variables could be either exogenous, or endogenously determined by some linear combination of other variables, or residuals that account for the variance of the endogenous variables not explained by exogenous and endogenous variables (Wright, 1960; Land, 1969).
follows the assumptions of the OLS regressions and later evolves into structural equation modeling (SEM) which uses the general linear modeling (GLM) approach to estimate non-recursive models, models with measurement error, and models with latent (unobserved) variables (Maruyama, 1998).  

We jointly model the relationships among accounting quality, bond liquidity, and the cost of debt as described in Figure 2. The model may be presented in equation forms as follows:

$$\%\text{NON\_ZERO}_j = p_{0,i} + p_{1,i} \times AQ_{i,j} + \epsilon_{i,j},$$

$$\text{NEG\_BIDASK}_{i,j} = p_{20,i} + p_{21,i} \times AQ_{i,j} + \epsilon_{i,j},$$

$$\text{YIELD\_SPREAD}_{i} = p_{30,i} + p_{31,i} \times AQ_{i,j} + p_{32,i} \times \%\text{NON\_ZERO}_{i,j} + p_{33,i} \times \text{NEG\_BIDASK}_{i,j} + \epsilon_{i,j},$$

Following common practice in many accounting studies (e.g. De Ruyter and Wetzels, 1999; Van der Stede, 2000), we treat all variables in the model as observed variables (not as latent variables with multiple indicators) and assume our empirical proxies are reasonable without measurement error.

We use SEM to obtain the total effect of accounting quality on the cost of debt, the direct effect of accounting quality on the cost of debt, and the indirect effect through liquidity. The total effect informs us how much the cost of debt changes as a result of changes in accounting quality, regardless of the mechanisms by which this effect may occur (Alwin and Hauser, 1975). The indirect effect through liquidity is the part of the total effect of accounting quality on the cost of debt that is mediated by liquidity, which we model as intervening variables between AQ and yield spreads.  

Since we include both $\%\text{NON\_ZERO}$ and $\text{NEG\_BIDASK}$ as liquidity measures, the indirect effect of AQ through liquidity is the sum of the indirect effects of AQ through

16 Non-recursive models refer to models that have two-way arrows between the same variables. A model in which all arrows are one-way is called a recursive model. Strictly speaking, only recursive models could be estimated using path analysis (Lleras 2005). Our model of accounting quality, liquidity, and the cost of debt in Figure 2 is a recursive model.

17 Again, we include both $\%\text{NON\_ZERO}$ and $\text{NEG\_BIDASK}$ in path analysis as in the multiple regressions to allow these measures to capture different dimensions of bond liquidity.
and \textit{NEG\_BIDASK}. The direct effect of accounting quality on the cost of debt is simply the part of its total effect that is not mediated by the intervening variables. It is calculated as the effect that remains when \textit{\%NON\_ZERO} and \textit{NEG\_BIDASK} have been held constant.

We acknowledge that the validity of the total, direct, and indirect effects reported in Panel A of Table 6 is conditioned on the correct specification of the model as described in Figure 2. It is likely that other variables, such as credit ratings, may also mediate the relation between accounting quality and the cost of debt. The model may become even more complex when additional variables are introduced into the model because of their possible interactions with liquidity. For this section, we focus our analysis on the mediating role of bond liquidity and analyze the parsimonious model between accounting quality, liquidity, and the cost of debt as laid out in Figure 2.

Panel A of Table 6 reports the standardized coefficients and \textit{p} values of SEM for the model depicted in Figure 2.\textsuperscript{18} We first note that the results in Panel A show a significant total effect of accounting quality on the cost of debt, consistent with the findings Section 5.2. The effect analysis further reveals a significant direct effect of accounting quality on the cost of debt and a significant indirect effect through \textit{\%NON\_ZERO} and \textit{NEG\_BIDASK}. The magnitudes of the direct and indirect effects are economically similar. For example, the total effect of \textit{DD} on yield spreads in our model is -0.233, of which, 55\% is the direct effect and 45\% comes through the indirect effect of bond liquidity. Results are similar when accounting quality is proxied by \textit{FLOS} and \textit{ADJFLOS}. Overall, the results of SEM (path analysis) indicate that accounting quality has both a direct effect and an indirect effect (through liquidity) of comparable magnitudes on the cost of debt.

\textsuperscript{18} The direct, indirect, and total effects are calculated with approximate \textit{p} values using the EFFPART statement in the PROC TCALIS step. The convergence criterion of the total and indirect effects is met, which guarantees the validity of the computation of the effects (Yung, 2008).
5.3.2. Decomposition of incremental explanatory power

Another way to assess the relative significance of accounting quality and bond liquidity in explaining yield spreads is to compare the explanatory power of accounting quality and liquidity in the cost of debt models. The Vuong’s likelihood ratio test (Vuong, 1989) is a directional and symmetric approach to test whether two competing models are equally close to the true specification against the hypothesis that one model is closer than the other. It is designed to make pair-wise comparisons to select the model closer to the “truth” based on the Kullback-Liebler information criteria (Kullback and Liebler, 1951). We first compute the Vuong’s statistics and test the null hypothesis of no difference in the ability of two contending sets of explanatory variables to explain variations in the cost of debt. We then decompose the explanatory power and compare the incremental explanatory power of accounting quality and liquidity in explaining variations in the cost of debt.

For each accounting quality measure, we estimate the following cost of debt regressions:

\[
YIELD\_SPREAD_{ij} = \alpha_{0,j} + \Pi \times Controls + \varepsilon_{ij} \quad \text{Model A}
\]
\[
YIELD\_SPREAD_{ij} = \beta_{0,j} + \beta_{AQ,j} \times AQ_{ij} + \Pi \times Controls + \varepsilon_{ij} \quad \text{Model B}
\]
\[
YIELD\_SPREAD_{ij} = \gamma_{0,j} + \gamma_{AQ,j} \times%NON\_ZERO_{ij} + \gamma_{NEG\_BIDASK,j} + \Pi \times Controls + \varepsilon_{ij} \quad \text{Model C}
\]
\[
YIELD\_SPREAD_{ij} = \lambda_{0,j} + \lambda_{AQ,j} \times AQ_{ij} + \lambda_{ZERO\_BIDASK_{ij}} + \lambda_{NEG\_BIDASK_{ij}} + \Pi \times Controls + \varepsilon_{ij} \quad \text{Model D}
\]

Model A is the benchmark model which regresses yield spreads on the control variables. The control variables are the same as in Section 5.1. Model B adds AQ to Model A and Model C adds two liquidity measures to Model A. Finally, Model D is the full model that includes accounting quality, the liquidity measures, and the control variables.

We conduct the Vuong’s test to compare the explanatory power between Model B, C, D, and the benchmark model A. We first test whether there is any difference in the R-squared of the
AQ model (Model B) and the benchmark model (Model A). Untabulated results show that the AQ model has significantly higher explanatory power than the benchmark model only in the case of $DD$. When AQ is measured by $FLOS$, we can’t reject the null hypothesis that the AQ model and the benchmark model have equal power to explain the cost of debt. When AQ is measured by $ADJFLOS$, the difference between the R-squared of the AQ model and that of the benchmark model is only marginally significant ($p$ value of 0.09). In contrast, the liquidity model (Model C) consistently has significantly higher explanatory power than the benchmark model, suggesting that including liquidity measures $\%NON\_ZERO$ and $NEG\_BIDASK$ materially increases the model’s power in explaining the cost of debt. We also test the null hypothesis of no difference in explanatory power between the full model and the AQ model and no difference between the full model and the liquidity model. The full model has significantly higher explanatory power than the AQ model for all three accounting quality measures, but not the liquidity models (except in the case of $DD$). These results, together with those in Section 5.2, suggest that although the coefficients of accounting quality are significant, adding accounting quality to the model does not increase the explanatory power in explaining variations of the cost of debt.

To further illustrate the break-up of the explanatory power of the model, we decompose the explanatory power into that corresponding to the total, direct, and indirect effects of AQ on the cost of debt. We subtract the R-squared of the benchmark model from that of the AQ model to compute the explanatory power corresponding to the total effect of AQ on the cost of debt. We subtract the R-squared of the liquidity model from that of the full model to compute the incremental explanatory power related to the direct effect of AQ on the cost of debt. The difference between them corresponds to the indirect effect of AQ on the cost of debt through liquidity.
Panel B of Table 6 reports the results of decomposing the incremental explanatory power. Most of the explanatory power of accounting quality in explaining the cost of debt comes from its indirect effect through liquidity. In the case of $DD$, the incremental explanatory power associated with the direct effect of $AQ$ is 0.35%, while the incremental explanatory power associated with the indirect effect is 0.44%. When measured by $FLOS$ and $ADJFLOS$, accounting quality has almost zero incremental explanatory power associated with its direct effect. Results of the Vuong’s test and decomposing the incremental explanatory power show that even when the coefficients of accounting quality are significant in directly and indirectly explaining the cost of debt, the explanatory power mainly comes from its indirect effect through bond liquidity.

6. Robustness check

To check whether our results are sensitive to the length of rolling windows we choose to calculate accounting quality measures, we calculate all three quality measures over the five-year and ten-year rolling windows and redo our analysis for the liquidity regressions and yield spread regressions. The results (untabulated) are similar for all three AQ measures calculated over five-year and ten-year rolling windows.

In Section 5.2, we include both liquidity measures in the cost of debt model. We further analyze the effect of AQ on the cost of debt with only one liquidity measure in the model. The results (untabulated) of yield spread models with $\%NON\_ZERO$ or $NEG\_BIDASK$ are similar to the results from the models that include both liquidity measures.
References


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. (2005) 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.
Figure 2

Figure 2 depicts the path diagram regarding the relations between accounting quality, bond liquidity (%NON_ZERO and NEG_BIDASK), and the cost of debt (YIELD_SPREAD).
<table>
<thead>
<tr>
<th>SELECTION CRITERIA</th>
<th>LOSS OF OBS</th>
<th>FINAL SAMPLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Datastream data</td>
<td>2,125 Firm-</td>
<td>2,125 Firm-</td>
</tr>
<tr>
<td>Datastream data with valid FISD</td>
<td>-52 Firm-</td>
<td>2,073 Firm-</td>
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<tr>
<td>Datastream data with valid FISD/COMPUSTAT records</td>
<td>-969 Firm-</td>
<td>1,104 Firm-</td>
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<tr>
<td>Quarterly bid and ask prices in Bloomberg</td>
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<td>499 Firm-</td>
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<tr>
<td>S&amp;P rating, non-negative total assets, non-negative book and market value of equity, and non-negative yield spreads</td>
<td>-18 Firm-</td>
<td>481 Firm-</td>
</tr>
<tr>
<td>Control variables</td>
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<td>424 Firm-</td>
</tr>
<tr>
<td>Accounting quality measures</td>
<td>-42 Firm-</td>
<td>382 Firm-</td>
</tr>
</tbody>
</table>

This table summarizes the sample selection process. We detail the number of observations lost due to each data requirement and the number of observations remaining in the sample after each data requirement. We report both the number of firms and the number of firm-years (fiscal years), the latter being the unit of our analysis. We start with bond-issuing firms from the Datastream database and merge the Datastream data with the Mergent Fixed Income Securities Database (FISD). Only the number of firms is available for these two steps because fiscal year data is not available before merging with Compustat. The sample is then matched with the Compustat data. We manually collect quarterly bid and ask prices for this sample from the Bloomberg terminals. Bond liquidity and cost of debt data is available for 499 firms (2574 firm-years). We exclude observations with missing Standard & Poor (S&P) bond credit ratings in FISD, negative total assets, negative book and market value of equity (Francis et al., 2005), and negative yield spreads in Datastream. We delete firms without Compustat data to calculate our control variables (book-to-market ratio, leverage, return on assets, current ratio, tangibility, and standard deviation of operating cash flows (see Table 2 for the definition of the control variables). Our final sample varies with the availability of time series data required to calculate different AQ measures, $DD$, $FLOS$, and $ADJFLOS$ (see Table 2 for the definition of these measures). The $DD$ sample consists of 1,814 firm-years, and the $FLOS$ sample and the $ADJFLOS$ sample consist of 2,105 firm-years.
<table>
<thead>
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<th>VARIABLE</th>
<th>DEFINITION</th>
</tr>
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<tbody>
<tr>
<td><strong>Accounting Quality</strong></td>
<td></td>
</tr>
<tr>
<td>$DD$</td>
<td>Accounting quality measure as developed in Dechow and Dichev (2002), which is the (negative) seven-year rolling standard deviation of the residuals from the regressions of current accruals on past, current, and future cash flows from operations. Larger values of $DD$ represent better accrual quality.</td>
</tr>
<tr>
<td>$FLOS$</td>
<td>Accounting quality measure as developed in Francis et al. (2005), which is the (negative) seven-year rolling standard deviation of the residuals from the cross-sectional regressions of current accruals on past, current, and future cash flows from operations. Larger values of $FLOS$ represent better accrual quality.</td>
</tr>
<tr>
<td>$ADJFLOS$</td>
<td>Accounting quality measure based on $FLOS$, adjusting for accrual volatilities. Calculated as the residuals from the regressions of $FLOS$ on the seven-year rolling standard deviations of current accruals. Larger values of $ADJFLOS$ represent better accrual quality.</td>
</tr>
<tr>
<td><strong>Bond Liquidity and Cost of Debt</strong></td>
<td></td>
</tr>
<tr>
<td>$%NON_ZERO$</td>
<td>Firm liquidity measure 1, calculated as the average percentage non-zero bond returns across bonds issued by the firm, weighed by offering amount. Larger values of $%NON_ZERO$ represent higher levels of liquidity.</td>
</tr>
<tr>
<td>$NEG_BIDASK$</td>
<td>Firm liquidity measure 2, calculated as the (negative) average of bid ask spreads across bonds issued by the firm, weighed by offering amount. Bid ask spreads are expressed in percentages. Larger values of $NEG_BIDASK$ represent higher levels of liquidity.</td>
</tr>
<tr>
<td>$YIELD_SPREAD$</td>
<td>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 $sp$). Larger values of $YIELD_SPREAD$ represent higher cost of debt.</td>
</tr>
<tr>
<td><strong>Bond Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>$AGE$</td>
<td>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.</td>
</tr>
<tr>
<td>$LOGAGE$</td>
<td>Logarithm of $AGE$.</td>
</tr>
<tr>
<td>$MATURITY$</td>
<td>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.</td>
</tr>
<tr>
<td>$LOGMATURITY$</td>
<td>Logarithm of $MATURITY$.</td>
</tr>
<tr>
<td>$OFFER$</td>
<td>Total offering amount, which is the sum of offering amount of bonds issued by the firm.</td>
</tr>
<tr>
<td>$LOGOFFER$</td>
<td>Logarithm of $OFFER$.</td>
</tr>
</tbody>
</table>
**RATING** Bond rating calculated as the weighted average bond rating across bonds issued by the firm, using offering amounts as weights. Individual bond ratings are the most updated (in the fiscal year) Standard and Poor bond credit ratings obtained from the Mergent FISD database.

**Firm Characteristics**

**BM** 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).

**CRATIO** Current ratio calculated as current assets (ACT in COMPUSTAT) divided by current liabilities (LCT in COMPUSTAT) at the end of year.

**LEV** 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.

**NUMAN** 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.

**LOGNUMAN** Logarithm of NUMAN.

**ROA** Return on assets calculated as operating income (OIADP in COMPUSTAT) over average total assets (AT in COMPUSTAT) for the year.

**SDACCR** Rolling standard deviation of current accruals over the past 7 years. 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), debt in current liabilities (DLC in COMPUSTAT).

**SDCFO** Rolling standard deviation of cash flows from operations over the past 7 years. Cash flows from operations are calculated as income before extraordinary items (IB in COMPUSTAT) plus depreciation and amortization (DP in COMPUSTAT) minus current accruals.

**SIZE** Total assets (AT in COMPUSTAT) at the end of the fiscal year.

**LOGSIZE** Logarithm of SIZE.

**TANGIBLE** 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.

Table 2 describes the variables used in the paper. We use three measures of accounting quality, our independent variable. We multiply the accrual quality measures developed in Dechow and Dichev (2002) and Francis et al. (2005) by -1 so that higher values of DD and FLOS represent better earnings quality. We construct two direct bond liquidity measures, the percentage of non-zero bond returns (%NON_ZERO) and negative bid ask spreads (NEG_BIDASK). For each proxy, we first calculate the liquidity measure at the bond level for all bonds issued by the firm, and then using offering amount as weights, compute the weighted average liquidity at the firm level. We multiply the bid ask spreads by -1 to make larger values of bid-ask spread represent higher levels of liquidity. The cost of debt measure is the weighted average yield spreads (YIELD_SPREAD). Bond yield spreads are obtained from Datastream, calculated as the difference of bond yield over the yield of the Treasury bill of the same maturity. We calculate four bond characteristics – bond age (AGE), offering amount (OFFER), bond maturity (MATURITY), and bond rating (RATING) at the firm level. Finally we use Compustat data to compute firm characteristics – the book-to-market ratio (BM), current ratio (CRATIO), leverage (LEV), the number of equity analysts (NUMAN), return on assets (ROA), the standard deviation of current accruals (SDACCR), the standard deviation of cash flows from operations (SDCFO), total assets (SIZE), and tangibility ratio (TANGIBLE).
Table 3
Summary Statistics of the Sample Firms

Panel A. Descriptive Statistics

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>STDDEV</th>
<th>5%</th>
<th>95%</th>
<th>%Pos</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accounting Quality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DD</td>
<td>-0.012</td>
<td>-0.009</td>
<td>0.01</td>
<td>-0.033</td>
<td>-0.003</td>
<td>0%</td>
</tr>
<tr>
<td>FLOS</td>
<td>-0.031</td>
<td>-0.026</td>
<td>0.019</td>
<td>-0.072</td>
<td>-0.010</td>
<td>0%</td>
</tr>
<tr>
<td>ADJFLOS</td>
<td>0.001</td>
<td>0.004</td>
<td>0.013</td>
<td>-0.026</td>
<td>0.017</td>
<td>65%</td>
</tr>
<tr>
<td>Bond Liquidity and Cost of Debt</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%NON_ZERO</td>
<td>75.00%</td>
<td>94.80%</td>
<td>30.90%</td>
<td>9.90%</td>
<td>96.30%</td>
<td>100%</td>
</tr>
<tr>
<td>NEG_BIDASK * (%)</td>
<td>-0.44</td>
<td>-0.38</td>
<td>0.20</td>
<td>-0.87</td>
<td>-0.22</td>
<td>0%</td>
</tr>
<tr>
<td>YIELD_SPREAD (%)</td>
<td>2.28</td>
<td>1.68</td>
<td>1.70</td>
<td>0.68</td>
<td>5.77</td>
<td>100%</td>
</tr>
<tr>
<td>Bond Characteristics</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>4.9</td>
<td>4.6</td>
<td>2.6</td>
<td>1.0</td>
<td>9.9</td>
<td>100%</td>
</tr>
<tr>
<td>MATURITY</td>
<td>16.1</td>
<td>13.6</td>
<td>7.2</td>
<td>8.4</td>
<td>31.0</td>
<td>100%</td>
</tr>
<tr>
<td>OFFER ($mils)</td>
<td>1,294</td>
<td>685</td>
<td>1,495</td>
<td>150</td>
<td>4,674</td>
<td>100%</td>
</tr>
<tr>
<td>RATING</td>
<td>5.9</td>
<td>6.0</td>
<td>1.1</td>
<td>4.0</td>
<td>7.0</td>
<td>100%</td>
</tr>
<tr>
<td>Firm Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BM</td>
<td>0.53</td>
<td>0.47</td>
<td>0.37</td>
<td>0.13</td>
<td>1.15</td>
<td>100%</td>
</tr>
<tr>
<td>CRATIO</td>
<td>1.40</td>
<td>1.26</td>
<td>0.67</td>
<td>0.56</td>
<td>2.69</td>
<td>100%</td>
</tr>
<tr>
<td>LEV</td>
<td>0.49</td>
<td>0.48</td>
<td>0.13</td>
<td>0.28</td>
<td>0.73</td>
<td>100%</td>
</tr>
<tr>
<td>NUMAN</td>
<td>18</td>
<td>17</td>
<td>10</td>
<td>4</td>
<td>38</td>
<td>100%</td>
</tr>
<tr>
<td>ROA</td>
<td>0.10</td>
<td>0.09</td>
<td>0.06</td>
<td>0.02</td>
<td>0.21</td>
<td>97%</td>
</tr>
<tr>
<td>SDACCR</td>
<td>0.022</td>
<td>0.016</td>
<td>0.017</td>
<td>0.005</td>
<td>0.058</td>
<td>100%</td>
</tr>
<tr>
<td>SDCFO</td>
<td>0.052</td>
<td>0.041</td>
<td>0.041</td>
<td>0.014</td>
<td>0.127</td>
<td>100%</td>
</tr>
<tr>
<td>SIZE ($mils)</td>
<td>13,301</td>
<td>6,860</td>
<td>16,654</td>
<td>1,061</td>
<td>42,754</td>
<td>100%</td>
</tr>
<tr>
<td>TANGIBLE</td>
<td>0.42</td>
<td>0.41</td>
<td>0.24</td>
<td>0.08</td>
<td>0.83</td>
<td>100%</td>
</tr>
</tbody>
</table>

Panel A Table 3 presents the descriptive statistics of the main variables. 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, and the percentage of positive values.

See Table 2 for variable definitions.

*NEG_BIDASK is negative because we multiply bond bid ask spreads by -1 to make large values represent better liquidity.
### Table 3 (Cont'd)

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

<table>
<thead>
<tr>
<th>VAR</th>
<th>DD</th>
<th>FLOS</th>
<th>ADJFL_O</th>
<th>NONZERO</th>
<th>NEG_B_DASK</th>
<th>YIELD_SPRE_ADS</th>
<th>AGE</th>
<th>MATURITY</th>
<th>OFFER</th>
<th>RATING</th>
<th>BM</th>
<th>CRATI</th>
<th>LEV</th>
<th>NUMAN</th>
<th>ROA</th>
<th>SDACC_R</th>
<th>SDCFO</th>
<th>SIZE</th>
<th>TANGIBLE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
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<td>(0.00)</td>
<td>(0.00)</td>
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</tr>
<tr>
<td>DD</td>
<td>1</td>
<td>0.51</td>
<td>0.41</td>
<td>0.19</td>
<td>0.15</td>
<td>-0.24</td>
<td>0.10</td>
<td>0.13</td>
<td>0.05</td>
<td>0.18</td>
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<td>-0.09</td>
<td>-0.05</td>
<td>-0.04</td>
<td>0.50</td>
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<td>0.16</td>
<td>0.07</td>
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<td>0.06</td>
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<td>-0.15</td>
<td>0.12</td>
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<td>-0.47</td>
<td>-0.39</td>
<td>0.07</td>
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<tr>
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<td>0.17</td>
<td>0.15</td>
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<td>-0.55</td>
<td>0.17</td>
<td>0.21</td>
<td>0.16</td>
<td>0.61</td>
<td>-0.16</td>
<td>-0.15</td>
<td>-0.24</td>
<td>0.20</td>
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<td>-0.17</td>
<td>-0.23</td>
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<td>0.01</td>
</tr>
<tr>
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<td>0.09</td>
<td>0.35</td>
<td>1</td>
<td>-0.42</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.45</td>
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<td>-0.11</td>
<td>-0.17</td>
<td>0.10</td>
<td>0.18</td>
<td>-0.10</td>
<td>-0.13</td>
<td>0.12</td>
<td>-0.04</td>
</tr>
<tr>
<td>DASK</td>
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<td>-0.23</td>
<td>-0.19</td>
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<td>0.13</td>
<td>0.35</td>
<td>-0.26</td>
<td>-0.37</td>
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<tr>
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<td>0.07</td>
<td>0.21</td>
<td>0.03</td>
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<td>1</td>
<td>0.50</td>
<td>0.06</td>
<td>0.19</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.24</td>
<td>0.11</td>
<td>0.07</td>
<td>-0.07</td>
<td>-0.11</td>
<td>0.20</td>
<td>-0.01</td>
</tr>
<tr>
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<td>-0.17</td>
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<td>-0.18</td>
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<td>0.08</td>
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<td>-0.16</td>
<td>0.29</td>
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<td>0.23</td>
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<td>0.02</td>
<td>0.27</td>
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<td>0.05</td>
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<td>-0.03</td>
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<td>-0.00</td>
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<td>-0.06</td>
<td>-0.22</td>
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</tr>
<tr>
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<td>0.02</td>
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</tr>
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<td>0.04</td>
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<td>0.11</td>
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<td>0.04</td>
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</tr>
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<td>0.05</td>
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</tr>
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<td>-0.11</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.26</td>
<td>0.06</td>
<td>-0.00</td>
<td>0.01</td>
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</tr>
<tr>
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<td>0.05</td>
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<td>0.67</td>
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<td>0.24</td>
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<td>-0.07</td>
<td>0.02</td>
<td>0.01</td>
<td>0.22</td>
<td>0.07</td>
<td>-0.03</td>
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<td>-0.10</td>
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<td>-0.22</td>
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<td></td>
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</tbody>
</table>

See Table 2 for variable definitions.
Table 4
Tests of the Association between Accounting Quality and Bond Liquidity

\[
\text{Liquidity}_{ij} = \beta_{A_Q} + \beta_{A_Q} \times \text{AQ}_{ij} + \beta_{\text{LOGAGE}} \times \text{LOGAGE}_{ij} + \beta_{\text{LOGMATURE}} \times \text{LOGMATURE}_{ij} + \beta_{\text{LOGOFFER}} \times \text{LOGOFFER}_{ij} + \beta_{\text{BM}} \times \text{BM}_{ij} + \beta_{\text{LEV}} \times \text{LEV}_{ij} + \beta_{\text{LOGNUMAN}} \times \text{LOGNUMAN}_{ij} + \beta_{\text{LOGSIZE}} \times \text{LOGSIZE}_{ij} + \beta_{\text{ROA}} \times \text{ROA}_{ij} + \beta_{\text{SDCFO}} \times \text{SDCFO}_{ij} + \text{YearDummies} + \text{IndustryDummies} + \varepsilon_{ij}
\]

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>Predicted sign</th>
<th>%NON_ZERO</th>
<th>NEG_BIDASK</th>
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<tr>
<td></td>
<td></td>
<td>DD</td>
<td>FLOS</td>
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<tr>
<td>AQ</td>
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<td>3.37</td>
<td>1.02</td>
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<td>(0.00)</td>
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<tr>
<td>LOGAGE</td>
<td>–</td>
<td>-0.02</td>
<td>-0.03</td>
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<tr>
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<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
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<tr>
<td>LOGMATURE</td>
<td>?</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>LOGOFFER</td>
<td>+</td>
<td>-0.03</td>
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<tr>
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<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
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<tr>
<td>BM</td>
<td>–</td>
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<tr>
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<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
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<tr>
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<td>-0.35</td>
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<tr>
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<td></td>
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</tr>
<tr>
<td>LOGNUMAN</td>
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<td>0.05</td>
<td>0.05</td>
</tr>
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<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
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<td>0.06</td>
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<td>(0.00)</td>
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<tr>
<td>ROA</td>
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<tr>
<td>SDCFO</td>
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<td>-0.64</td>
<td>-0.81</td>
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<tr>
<td>Year Dummies, Industry Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>1,684</td>
<td>1,969</td>
</tr>
<tr>
<td>ADJ-RSQ</td>
<td></td>
<td>59.26%</td>
<td>57.76%</td>
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</table>

Table 4 reports results of the liquidity regressions, with two-sided \( p \) values reported in parentheses below the coefficients. To control the effects of outliers, we delete observations with absolute standardized residuals greater than two. Model 1 and 4 have \( DD \) as the independent variable. The sample initially consists of 1,814 firm-years, and after excluding the outliers, reduces to 1,684 in Model 1, and to 1,774 in Model 4. The independent variable in Model 2 and 5 is \( FLOS \). The sample reduces to 1,969 in Model 2 and to 2,039 in Model 5 after excluding the outliers from the sample of 2,105 firm-years. The independent variable in Model 3 and 6 is \( ADJFLOS \). The sample reduces to 1,971 in Model 3 and to 2,039 in Model 6 after excluding outliers. See Table 2 for variable definitions.
Table 5 reports the estimation results of the cost of debt regressions. The dependent variable is the cost of debt $YIELD\_SPREAD_{ij}$. For each AQ proxy, we include liquidity measures $\%NON\_ZERO_{ij}$ and $NEG\_BIDASK_{ij}$ in one model and include no liquidity measure in the other. To reduce the effect of outliers and keep the samples constant for comparison, we delete observations with absolute standardized residuals greater than two in either regression.
AQ in Model 1 and 2 is proxied by $DD$. Liquidity measures are included in Model 1 and not in Model 2. The sample size reduces to 1,700 from 1,814 after the outlier treatment. The difference between the coefficients of $DD$ in Model 1 and Model 2 is reported in the row $DIFF$, with the $p$ value given below. AQ in Model 3 (with liquidity measures) and Model 4 (without liquidity measures) is proxied by $FLOS$. The sample size changes from 2,105 to 2,054 due to the outlier treatment. The difference between the coefficients of $FLOS$ in Model 3 and Model 4 is reported in the row $DIFF$, with the $p$ value given below. AQ in Model 5 (with liquidity measures) and Model 6 (without liquidity measures) is proxied by $ADJFLOS$. Excluding the outliers reduces the sample size from 2,105 to 2,053. The difference between the coefficients of $ADJFLOS$ in Model 3 and Model 4 is reported in the row $DIFF$, with the $p$ value given below.
Table 6
Direct and Indirect Effects of Accounting Quality on the Cost of Debt

<table>
<thead>
<tr>
<th></th>
<th>PANEL A</th>
<th></th>
<th>PANEL B</th>
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<tbody>
<tr>
<td></td>
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<td>DECOMPOSITION OF INCREMENTAL EXPLANATORY POWER</td>
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<tr>
<td></td>
<td>DD</td>
<td>FLOS</td>
<td>ADJFLOS</td>
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<tr>
<td>DIRECT AQ</td>
<td>-0.127</td>
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<td>-0.089</td>
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<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>INDIRECT THROUGH LIQUIDITY</td>
<td>-0.106</td>
<td>-0.097</td>
<td>-0.087</td>
</tr>
<tr>
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</tr>
<tr>
<td>TOTAL AQ</td>
<td>-0.233</td>
<td>-0.185</td>
<td>-0.176</td>
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<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

Table 6 describes the direct and indirect effects of accounting quality on the cost of debt. Panel A reports the results of SEM that analyze the relations between accounting quality, bond liquidity, and the cost of debt depicted in Figure 2. Panel B presents the results of the decomposition of incremental explanatory power. We decompose the explanatory power into that corresponding to the total, direct, and indirect effect of AQ on the cost of debt. We subtract the R-squared of the benchmark model from that of the AQ model to compute the explanatory power corresponding to the total effect of AQ on the cost of debt. We subtract the R-squared of the liquidity model from that of the full model to compute the incremental explanatory power related to the direct effect of AQ on the cost of debt. The difference between them corresponds to the indirect effect of AQ on the cost of debt through liquidity.