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CORPORATE TRANSPARENCY AND BOND LIQUIDITY

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WORKING PAPERS ON FINANCE NO. 2014/4

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

FEBRUARY 2014

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February 2014

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To answer the question what causes an asset to be illiquid, we analyze the impact that transparency of corporate accounting information has on the liquidity of its traded bonds. In particular, we focus on how this relationship depends on aggregate liquidity and the financial state of the firm. We use an extensive panel data set comprising more than 40,000 quarterly bond observations between 2004Q4 and 2012Q4. We find a statistically and economically significant impact of transparency on bond liquidity. This relationship becomes stronger during times of financial distress. We also find that the impact of transparency on liquidity is much larger than the influence of credit risk. Finally, we also find that transparent accounting information has a strong effect on liquidity risk.

Keywords: Corporate Bonds, Liquidity, Transparency, Information Quality, Financial Crises.
JEL classification: C23, G01, G12, G30, M41.

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Abstract

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1 Introduction

This study is motivated by two topics that have received a lot of attention in the recent empirical literature: the importance of liquidity on the corporate bond market on the one hand and the impact that accounting transparency has on the liquidity of stocks on the other. Both areas of research have explicitly examined how the recent financial crisis has affected asset markets. This study is the first to combine these two areas by investigating the relationship between the transparency of firm-level accounting information and the level and variability of liquidity of its traded bonds.

The research on the impact of liquidity on corporate bonds focuses mostly on pricing issues. Several recent studies have examined how much of the cross-section of corporate bond spreads are attributable to credit and liquidity risk. Lin et al. (2011) examine the pricing of liquidity risk in the cross-section of bond returns. They find that market-wide liquidity risk is a priced state-variable in the corporate bond market. Bao et al. (2011) find market-wide liquidity to be the dominant factor in explaining the time variation of the aggregate bond market, especially during the financial crisis. They also find that liquidity explains a substantial part of the cross-sectional variation in bond spreads. Dick-Nielsen et al. (2012) explicitly examine the impact of the financial crisis before and after the subprime crisis. They document that liquidity effects have become more important after the onset of the crisis. Similarly, Friewald et al. (2012) find that the economic impact of liquidity measures is significantly larger in periods of crisis. Common to all these studies is the conclusion that liquidity has first-order effects on bond markets and that liquidity risk is a priced factor in bond returns (some studies suggest that liquidity risk is as important as credit risk). What these studies do not explain, however, is why a particular bond is traded more or less liquidly.

A large literature is concerned with explaining the level of liquidity of assets. At least since Bagehot (1971), it has been recognized that a primary cause of illiquidity in financial markets is the adverse selection which arises from the presence of privately informed traders. The theoretical implications of the adverse selection paradigm for financial market equilibrium have been analyzed extensively. Diamond and Verrecchia (1991) argue that to the extent that the release of accounting information can reduce information asymmetry in the market place such information can improve liquidity. A number of studies have therefore analyzed the level of liquidity around the release of accounting information (Lee et al., 1993; Kim and Verrecchia, 1994; Affleck-Graves et al., 2002) and the impact of private information (Vega, 2006; Francis et al., 2007). Several works also discuss the relation between disclosure policy and liquidity (Brown and Hillegeist, 2007; Brown et al., 2004).

Several recent papers have started to explore the relationship between the transparency of corporate accounting numbers and the liquidity of a company's assets. In contrast to our paper, these studies have focused on the liquidity (Lang and Maffett, 2011) and liquidity risk (Lang and

Maffett, 2011; Ng, 2011) of equity. Compared to bond returns, stock returns are less sensitive to their liquidity. Brennan and Subrahmanyam (1996) report that on average, stocks with high levels of liquidity have a 9.12 percent higher annual return than stocks with low levels of liquidity. The average return in their sample is 12 percent annually.[1] For liquidity risk, Pastor and Stambaugh (2003) found that the risk-adjusted average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5 percent annually. During their sample period, the average annual return of the monthly value-weighted CRSP index was 22.2 percent. In comparison, using the same method as Pastor and Stambaugh (2003), Lin et al. (2011) find that the average return on bonds with high sensitivities to aggregate liquidity exceeds that for bonds with low sensitivities by about 4 percent annually. The average return on the bonds is only 1.93 percent annually though. In relative terms, liquidity risk plays a much larger role for bond returns.

While private information in the stock market is predominantly inside information about a firm's cash flows, private information in the bond market mainly derives from heterogeneous interpretation of public information (Green, 2004; Brandt and Kavajecz, 2004) or private observations of investors' order flows by dealers (Lyons, 2001). Though investors observe the same set of public information, they differ in their abilities to analyze the information. For example, a large investment bank may have more skilled analysts or use more sophisticated models to analyze public information than a pension fund. This heterogeneity can create information disparity among traders similar to the effect of private information in the traditional sense. Pasquariello and Vega (2007) examine the role of private and public information in the process of price formation in the U.S. Treasury market and find that daily bond price dynamics are related to fundamentals and agents' beliefs. These studies highlight the importance of asymmetric information in bond markets.

Prior research on bond liquidity has focused either on the impact of bond characteristics (bond age, maturity, issue size, coupon) on its liquidity or the impact of liquidity risk on credit spreads. We complement these studies by investigating the cross-sectional differences in liquidity and liquidity risk. We find that firms with greater transparency have bonds that trade at significantly higher levels of liquidity. Hence, to the extent that liquidity affects the cost of capital, transparent accounting information decreases the cost of debt.

We also find that the relationship between accounting transparency and bond liquidity is non-linear. This is especially true for firms in financial distress, either measured by credit rating or by the probability of default. Our analysis seems to confirm the theory by Dang et al. (2012) that the information sensitivity of trades is state dependent. As long as bonds are relatively safe, debt is an information insensitive asset. However, as market conditions (such as a financial crisis)

[1] These estimates are based on Table 3 in Brennan and Subrahmanyam (1996) from which we calculate the return premium in their sample as the difference between the high liquidity portfolios (λ group 5) and the low liquidity portfolios (λ group 1). The average return is the average of all portfolios.

or firm conditions (such as the likelihood of default) deteriorates, debt becomes increasingly information sensitive.

Finally, we also document that transparency has a strong impact on (total) liquidity risk of bonds. As liquidity risk is a large component of bond spreads, accounting transparency has a direct impact on the riskiness of bonds.

This paper contributes to the literature about the effects of asymmetric information on financial markets. In particular, we contribute to the literature of effects of disclosure quality on market liquidity as well as the of accounting transparency on cost of capital, surveyed in Healy and Palepu (2001) and Leuz and Wysocki (2008). Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) argue that for firms with transparent accounting information, investors can be relatively more confident that stock transactions occur at fair prices which increases the liquidity of the stock. This argument is substantiated in a number of empirical papers (such as Welker (1995) or Leuz and Verrecchia (2000)). We extend the existing literature by showing that the argument extends to debt markets. Our results show a large increase of the liquidity of bonds for transparent firms, indicating that transparency reduces information asymmetry in bond markets and that a policy of higher quality disclosures improves the liquidity of a firm's bonds.

The remainder of this paper is organized as follows. Section 2 discusses the prior literature which motivates this paper. In Section 3 we develop the hypotheses that are tested. Section 4 describes the data and Section 5 describes the statistical methodology and the empirical results of the paper. Section 7 concludes and provides suggestions for further research.

2 Literature Review

Our primary interest is in the relationship between firm-level transparency and the level and variability of the liquidity of the bonds issued by the firm.[2] To our knowledge, this is the first study that analyzes these relations. Recent research in financial economics has focused strongly on the impact of both firm-level and systematic liquidity on asset prices. This research has made it abundantly clear that liquidity has first-order effects and cannot be ignored. In light of this research, it seems desirable to understand why particular assets are traded more or less liquidly and to quantify the effects. There are a number of theoretical reasons why transparency of information should affect liquidity on asset markets which we review in this section. We also present empirical results of similar studies on the stock market.

[2] In this paper, we address the relationship of transparency and liquidity. We do not investigate how transparency of accounting information influences credit spreads. Consistent with the incomplete accounting information model of Duffie and Lando (2001), Yu (2005) finds that firms with higher disclosure rankings tend to have lower credit spreads. This transparency spread is especially large for short-term bonds.

Theories of disclosure quality typically focus on the effect on (stock market) liquidity, the cost of capital, or firm valuation. Liquidity is affected by disclosure quality because information asymmetries among investors induces adverse selection (Verrecchia, 2001). Less informed investors have to be concerned about trading with privately or better informed investors. As a consequence, uninformed investors require a price discount (premium) for buying (selling) the stock to protect themselves against losses from trading with an informed counterparty. This increases the bid-ask spread in secondary markets. At the same time, adverse selection reduces the number of shares that uninformed investors are interested in trading. Both effects decrease the liquidity of stock markets. At the same time, these effects can impact the cost of capital and hence firm value. Illiquidity and bid-ask spreads impose additional trading costs on investors, which need to be compensated in equilibrium increasing the required rate of return on securities (Constantinides, 1986; Amihud and Mendelson, 1986). Additionally, as argued by Garleanu and Pedersen (17), adverse selection potentially distorts investors' trading decisions thereby resulting in inefficient asset allocations. This leads to higher required rates of return in equilibrium.

An early view on illiquidity in financial markets is offered by Bagehot (1971) who argues that its causes lie in the adverse selection which arises from the presence of privately informed traders. The theoretical implications of adverse selection on equilibrium in financial markets has been extensively analyzed. There seems to be consensus both in the theoretical and empirical market micro structure literature that greater information asymmetry reduces stock liquidity (Brennan and Subrahmanyam, 1995; Verrecchia, 2001). Easley et al. (2002) find that the probability of information-based trades carries a positive premium in asset prices. This point of view is also emphasized in the review by Amihud et al. (2005). In summary, to the extent that transparent information about the company can reduce adverse selection problems it should increase liquidity.

Another source of illiquidity, emphasized in the search-frictions model of Duffie et al. (2005), is the difficulty of locating a counterparty who is willing to trade a particular security, or a large quantity of a given security. Further, once a counterparty is identified, the agents must negotiate the price in a less than perfectly competitive environment since alternative trading partners are not immediately available. This search friction is particularly relevant in over-the-counter (OTC) markets in which there is no central marketplace. A searching trader incurs financing costs or opportunity costs as long as his trade is delayed, and, further, he may need to give price concessions in the negotiation with the counterparty that he eventually finds. Alternatively, he may trade quickly with a dealer and bear illiquidity cost. In general, a trader faces a tradeoff between search and quick trading at a discount. The implications for asset pricing of search-frictions are discussed in Duffie et al. (2007).

On the empirical side, we identify three strands of literature that relate accounting transparency and stock liquidity. First is the literature on transparency and the level of liquidity, surveyed in Amihud et al. (2005) and Lang and Maffett (2011), which investigates the role of transparency in mitigating information asymmetry. Closely related is the theoretical research investigating liquidity variability and covariability, such as Brunnermeier and Pedersen (2009) and Vayanos (2004), which suggests mechanisms that cause liquidity to fluctuate, evaporate suddenly and covary with market-wide returns and market-wide liquidity. Further, Acharya and Pedersen (2005) provide theoretical and empirical evidence that the covariability of firm-level liquidity with market liquidity and market returns are systematic risk factors that are components of cost of capital. Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) argue that voluntary disclosure reduces information asymmetries among informed and uninformed investors. As a result, for firms with high levels of disclosure, investors can be relatively confident that any stock transactions occur at a fair price, increasing liquidity in the firms stock. In addition, these studies argue that expanded disclosure and stock liquidity will be associated with increased institutional ownership.

As discussed in Lang and Maffett (2011), by reducing uncertainty about intrinsic value, transparency has the potential to affect liquidity variability. Models in papers such as Brunnermeier and Pedersen (2009) and Vayanos (2004) show liquidity can dry up because of a flight to quality, where liquidity providers flee from assets with high levels of uncertainty about fundamental value. To the extent that transparency provides information it reduces uncertainty about intrinsic value, potentially reducing the sensitivity of liquidity to market shocks. Further, transparency effects are likely to be particularly pronounced during crisis periods. During large market downturns, liquidity tends to be particularly fragile because capital is scarce and overall uncertainty is high. As a result, opaque assets will be particularly sensitive to the effects of exogenous shocks to liquidity. Vayanos (2004) suggests that liquidity providers become more risk averse in the face of uncertainty about fundamental asset values. To the extent that transparency reduces uncertainty it has the potential to reduce the tendency to withdraw liquidity during market downturns. More recently, Lang et al. (2012) have documented that greater firm-level transparency lowers transaction costs and increases liquidity on equity markets. Lang and Maffett (2011) show that transparency reduces firm-level liquidity uncertainty, while Ng (2011) shows that increased information quality can reduce a firm's exposure to systematic liquidity risk.

In terms of empirical research, Pastor and Stambaugh (2003) find that the correlation between firm-level returns and market-wide liquidity is a priced risk factor. Ng (2011) provides evidence that accounting-level transparency measures are related to equity liquidity risk. Lang and Maffett (2011) focus on variation and covariation in firm-level liquidity. They document that liquidity variability and covariability have separable and incremental effects on firm value. Healy et al. (1999) find that firms that expand disclosure experience significant contemporaneous increases in stock prices that are unrelated to current earnings performance. Gelb and Zarowin (2002) find that firms with high disclosure ratings have high stock price associations with contemporaneous and future earnings relative to firms with low disclosure ratings. These findings suggest that firms disclosure strategies affect the speed with which information gets into prices. Also, several studies attempt to measure stock liquidity and to examine its relation to firm disclosure proxies. For instance, Welker (1995) documents a significant negative relation between analysts ratings of firms disclosures and bid–ask spreads. To summarize, while there are related empirical literatures, none addresses the central question of our paper which is whether, when and to what extent firm-level transparency affects the level and mitigates the variability of bond liquidity.

3 Hypotheses Development

In this section, we provide an overview of the questions that we investigate and formulate the hypotheses that we test. These all focus on the effect that transparency of balance sheet items has on the liquidity of corporate bonds.

H1: Higher transparency of accounting information leads to higher levels of liquidity for bonds.
Dang et al. (2012) make the observation that a security's information intensity varies with news accruing about the quality of the asset or issuer: As long as there is no doubt about the solvency of an issuer, ex ante information has little value or impact on trades. However, when doubts about the solvency of a borrower are raised, information acquisition becomes profitable for potential investors. This leads to adverse selection which dries up liquidity. In a similar manner, models of trade in OTC markets, such as Duffie et al. (2007), argue that transaction costs due to search frictions and information asymmetry are the cause of illiquidity. To the extent that transparent accounting information can reduce this asymmetry, we expect to find a negative relationship between measures of transparency and measures of illiquidity.

H2: The impact of transparency on bond liquidity is non-linear.
Dang et al. (2012) argue that the impact of information on bond markets is inherently asymmetric: Good news about the issuer has little effect. Bad public news about fundamentals, however, can cause the market value of debt to drop. This mechanism can cause debt to become information-sensitive and give agents an incentive to learn about tail risk. This effect is amplified when the asset is opaque leading to a non-linear relationship between transparency and liquidity.

H3: The effect of transparency on bond liquidity is more pronounced in periods of financial distress.
Several studies have indicated that liquidity of bond markets is strongly affected by flight-to-quality. Acharya et al. (2013), for example, argue that the price decrease due to increases in illiquidity during the financial crisis is lower for investment grade bonds. Similarly, Chen et al. (2007) and Friewald et al. (2012) provide empirical evidence for this flight-to-quality. In addition, as argued by Brunnermeier and Pedersen (2009), funding for liquidity providers tends to dry up during downturns because uncertainty is higher and funding is scarcer. Opaque

companies are likely to be more affected because greater uncertainty about intrinsic value means that it is more difficult and expensive for speculators to borrow to provide liquidity and their own capital is relatively low. In addition, the model in Dang et al. (2012) implies that during times of financial distress debt, which is generally information insensitive, suddenly becomes an information acquisition sensitive asset.

H4: Higher transparency of accounting information leads to lower variability of illiquidity for bonds.
Brunnermeier and Pedersen (2009) and Vayanos (2004) suggest that liquidity in assets with a great deal of uncertainty about fundamental value can be fragile in the sense that illiquidity can spiral upwards unexpectedly making trades prohibitively expensive. To the extent that transparency reduces uncertainty about fundamental value, liquidity tends to be less predictable and more sensitive to factors such as economy-wide uncertainty, funding availability, and risk aversion. Hence we expect that higher transparency leads to lower variability of illiquidity.

4 Data Description

Our sample consists of quarterly observations from Q4 2004 until Q4 2012. We obtain bond trading data from the TRACE database which has been disseminating all secondary over-the-counter corporate bond transactions of the members of the Financial Industry Regulatory Authority since October 2004. We filter the raw TRACE data as described in Dick-Nielsen (2009) to eliminate potentially erroneous data entries. We also apply the median filter and reversal filter from Edwards et al. (2007). Finally, we exclude all retail-sized trades (i.e., trades below $ 100,000 in value).

We obtain bond information from the FISD database, quarterly accounting data from Compustat, daily equity data from CRSP, and monthly EPS forecasts from the IBES database. After matching the data of all databases[3] and removing entries with missing values, we are left with data for 695 companies with a total of 3,550 bond issues. We only consider senior bonds with at least 90 days of maturity left and which are at least 90 days old at the beginning of a quarter. We also exclude all bonds with a rating of C or a default rating. Our final data set consists of 40,012 quarter-bond observations.

In the remainder of this section, we present the models and describe the empirical methodologies that underlie our measures of bond liquidity and firm-level transparency. We first describe the measures of liquidity and liquidity risk following Dick-Nielsen et al. (2012). Then we explain our methodology in measuring the transparency of accounting information from public sources

[3] We use the CRSP/Compustat merged database to match gvkeys and permnos. We match the IBES data based on the 9-digit CUSIP. We match TRACE and FISD data based on the 9-digit CUSIP of the bond issues. Finally, we merge the firm- and bond-level identifiers using the 6-digit company CUSIP and the exchange ticker. Only if both identifiers match we use the data.

following Lang et al. (2012) and Ng (2011). Finally, we present the controls we use to control for bond characteristics, credit risk and equity factors.

4.1 Measures of Bond Liquidity

As noted by Amihud and Mendelson (2008), transaction costs and liquidity are related but separate concepts. From an investors perspective, both the direct transaction costs of trading in a firms shares as well as the ability to form and liquidate a substantial portfolio in a timely manner are potentially important determinants of the price one is willing to pay for an asset. As there is no consensus on how to measure liquidity of an asset, we use three proxies for the illiquidity of a bond. Each variable is defined so that a higher value implies a higher level of illiquidity.[4]

The first proxy we use is the Amihud (2002) illiquidity measure which measures the price impact of a trade per unit traded. Price impact is a major consideration to investors contemplating an investment in a bond because it reduces the potential return by increasing roundtrip transactions costs. Further, this measure is consistent with theoretical research such as Grossman and Merton (1988) and Brunnermeier and Pedersen (2009), which defines liquidity based on price deviations from fundamental value as a result of buying and selling pressure.

The other two measures for liquidity that we use are proxies for the bid–ask spread of a bond. The first is the Roll (1984) which is based on the observation that the bid–ask spread can be extracted from the covariance between consecutive returns. The second measure is the Imputed Roundtrip Costs (IRC) of Feldhütter (2012). Imputed Roundtrip Trades are based on finding two trades close in time that are likely to be a buy and a sell. These trades are used to construct the IRC.

Finally, we measure (total) liquidity risk by the standard deviation of these three proxies. By doing so, we do not differentiate between systematic and unsystematic risk. Since we are not examining the pricing of bonds, this issue should not pose a problem for our research question.

4.2 Measures of Transparency

Because transparency is inherently difficult to measure and has many potential facets, we consider several measures.[5] For our first transparency variable, we follow Lang and Maffett (2011) and Lang et al. (2012) and estimate the degree to which a firm engages in discretionary earnings management by combining two commonly used measures of earnings management: The variability of net income relative to cash flow and correlation between accruals and cash flows. The underlying argument is that earnings management is manifested in the use of accruals to smooth out fluctuations in underlying cash flows. Since clearly there are non-discretionary components

[4] Appendix A describes the measures and their implementation in more detail.
[5] Appendix B describes the measures and their implementation in more detail.

to earnings smoothness (Jones, 1991), we first regress out a set of fundamental determinants of earnings smoothness and use the resulting residuals to form our measure of discretionary earnings smoothness. Our analyses include both the portion of smooth earnings explained by the intrinsic fundamental factors (*FES*) as well as the excess portion (*DES*). Our primary interest is in *DES* as a measure of transparency, and we predict that greater discretionary smoothing will be indicative of greater earnings management and therefore associated with greater opacity. However, we expect *FES* to be positively correlated with liquidity to the extent that there is less potential for asymmetric information in firms whose profits are naturally smooth. Lang et al. (2012) show that *DES* captures elements of managerial discretion in that it is positively correlated with incentives to manage earnings (concentrated ownership and high book-tax accounting conformity) and negatively correlated with impediments to earnings management (high quality auditor, strong investor protection, global accounting standards, and high analyst following).

As noted by Verrecchia (2001), disclosure theories generally predict that uncertainty surrounding firm value and adverse selection among investors is higher when information precision is lower. Following Ng (2011), we use earnings as a source of information for investors. Less volatile earnings are presumably more precise and are expected to be, on average, of higher quality. Consistent with this argument, Dichev and Tang (2009) show that more precise earnings are associated with higher earnings predictability after controlling for a variety of economic characteristics. Hence, we use earnings precision (*EP*) measured as the volatility in reported earnings as a proxy for transparency. As suggested by Dechow and Dichev (2002) and Francis et al. (2005), earnings with an accrual component that map with less variability into the cash flow component may be considered more informative. Therefore, we use accruals quality (AQ) as an additional measure of transparency. Several papers indicate that analysts gather and aggregate information from public and private sources to assess firm value, improving overall transparency (Brennan and Subrahmanyam, 1995; Lang and Lundholm, 1996; Lang et al., 2012). To the extent that analysts serve as information intermediaries, their presence should increase transparency. Hence, we include the number of analysts (*Analyst*) providing an annual EPS forecast for a given firm in a given quarter as a proxy for transparency.

When investors rely on analysts earnings forecasts to evaluate a firm, they are likely to regard forecasts as having greater precision if there is greater consensus/agreement among analysts (Lang and Lundholm, 1996; Barron et al., 1998; Diether et al., 2002; Zhang, 2006). Similar to Zhang (2006), we measure the *Precision* of agreement among analysts in terms of their forecasts as the negative of the inter-analyst standard deviation deflated by the stock price at the time when the standard deviation is computed. We require that at least three analysts cover the firm.[6]

[6]Research by Francis (2004) and Fan and Wong (2005) suggests that the informativeness of accounting data is likely to be higher if such data are audited by an affiliate of a global accounting firm. We therefore tried to include an indicator variable if a firms auditor is affiliated with a Big-4 audit firm. For our matched sample, we found that more than 99% of our observations were audited by a Big-4 firm.

4.3 Control Variables

We rely on the many prior studies that have examined determinants of liquidity. Among them are Garbade and Silber (1979), Sarig and Warga (1989), Chakravarty and Sarkar (1999), Stoll (2000), Schultz (2001), Brandt and Kavajecz (2004), Houweling et al. (2005), and Longstaff et al. (2005). Collectively, these studies suggest that the level of liquidity of a bond is dependent on the bond's age, its maturity, the issue size, and its coupon rate. Bond markets are generally characterized by a on-the-run effect in that young bonds tend to be traded more liquidly than more mature bonds. Similarly, long-maturity bonds tend to be less liquid than bonds with short maturities. Larger issues and higher coupon rates are generally associated with higher liquidity. We control for these characteristics as these are mostly related to clientele effects (see Amihud and Mendelson (1986)).

To control for credit risk, we follow Blume et al. (1998) and use the ratio of operating income to sales (*IS*), long term debt to assets (*DA*), total debt to capitalization (*DC*), the book-to-market (*BM*) ratio, and four pre-tax interest coverage (*IC*) range variables to the regressions.[7] Additionally, we obtain bond ratings from Standard and Poor's. If this rating is missing, we use the rating from Moody's and if this is missing, the rating from Fitch. If we still do not have a rating we use the company rating. Prior studies indicate that equity risk impact credit risk and liquidity (Bao et al. (2011), Lin et al. (2011), Dick-Nielsen et al. (2012)). We therefore include equity risk (*Vola*), measured as the volatility of daily stock returns in a given quarter.

5 Empirical Results

5.1 Canonical Correlation Analysis

In this paper we are attempting to link corporate transparency and bond liquidity. Both concepts are difficult to measure empirically, which is why we use a set of different proxies for each. To obtain a picture of the relationship between the two sets of variables, we use canonical correlation analysis (CCA). CCA seeks to identify possible links between two sets of variables $X \in \mathbb{R}^p$ and $Y \in \mathbb{R}^q$. As such, it is an extension of the classical bivariate correlation. In contrast to multivariate regression, it can be used when there are multiple dependent variables that are to be predicted by the independent variables. The canonical correlations between X and Y are found by finding the linear combinations which result in the highest correlation. The first

[7] The pre-tax interest coverage variables are defined as follows. We define the pre-tax interest rate coverage (*IC*) ratio as EBIT divided by interest expenses. It expresses how easily the company can cover its interest rate expenses. However, the distribution is highly skewed. As in Blume et al. (1998), we control for this skewness by creating four separate variables which allows for a non-linear relationship. First, the *IC* ratio is truncated by setting all negative values to 0 and all values above 100 to 100. The first variable (*IC5*) is set to the IC ratio if it is less than 5 and 5 if it is above. The second variable (*IC10*) is set to zero if IC is below 5, to the IC ratio minus 5 if it lies between 5 and 10, and 5 if it lies above. The third variable (*IC20*) is set to zero if IC is below 10, to the IC ratio minus 10 if it lies between 10 and 20, and 10 if it lies above. The fourth variable (*IC30*) is set to zero if IC is below 20 and is set to IC minus 20 if it lies above 20.

canonical correlation is the maximal correlation between any linear combinations of $\mathbf{X} \in \mathbb{R}^p$ and $\mathbf{Y} \in \mathbb{R}^q$:

$$\rho_c^1 = \max_{\mathbf{a}\in\mathbb{R}^p, \mathbf{b}\in\mathbb{R}^q} \operatorname{corr}(\mathbf{a}'\mathbf{X}, \mathbf{b}'\mathbf{Y}) \tag{1}$$

The linear combinations produced are called first canonical variates. The successive canonical correlations, up to the smaller of p and q, are constructed in the same manner with the additional requirement that every canonical variate of each set of covariates is orthogonal to all prior canonical variates of that set. The square of the canonical correlations, called canonical roots, represent the amount of variance in one canonical variate accounted for by the other canonical variate.

5.2 Panel Data Regression

Our data set consists of the quarterly time series data for each bond. The dependent variables to be explained are the different measures of bond liquidity. Our main independent variables are the proxies for company level transparency. We add controls for bond characteristics which are known to affect liquidity and credit risk to the regressions. To ensure that the information of the accounting information is contained in the bond trades, all independent variables are lagged by one quarter. To control for unobserved effects of our variates, we perform fixed-effects regressions with both bond-fixed and time-fixed effects.[8] The model we investigate is therefore given by

$$\begin{aligned} \text{Illiquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Characteristics}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}. \end{aligned} \tag{2}$$

As we are using a panel of data with possible multiple bonds per firm we use two-way clustered standard errors, at the firm-level and the time-dimension (Petersen, 2009). Since we use fixed-effects regression, we cannot use independent variables which do not change over time (coupon, offering amount, industry dummies). We also cannot use age and maturity at the same time since they are linearly related over time for each bond. As it is more common in the bond liquidity literature, we retain bond age in our regressions. The effects of all these variables will be subsumed in the fixed effects. As we are interested in determining the impact of accounting transparency on bond liquidity and not the impact of these constant variables, we do not consider this to be an issue.

5.3 Summary Statistics

This section provides summary statistics for our matched sample of the US corporate bond market (see Section 4). Table 1 reports the cross-sectional variation of the variables used in

[8] The coefficients are estimated using the within estimator in order to account for variation in bond liquidity that is unrelated to our proxies. As would be expected, the Hausman and LM tests strongly reject the null hypothesis of zero correlation between the effects and our regressors.

Table 1: Summary Statistics

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, and standard deviation) for the liquidity and transparency proxies as well as our control variables. *Amihud* is the Amihud (2002) measure of illiquidity, *Roll* the bid–ask spread proxy by Roll (1984), and *IRC* the imputed roundtrip costs of Feldhütter (2012). *DES* is a measure of discretionary earnings smoothing, while *FES* measures the fundamental smoothness of earnings that naturally occur following Lang et al. (2012). *EP* measures earnings precision and *AQ* accruals quality according to Ng (2011). *Analyst* are the number of analysts giving earnings forecasts for company and *Precision* is the negative of the standard deviation of these forecasts scaled by the stock price. *Age* is the time in years since a bond was issued, *Maturity* its time in years until it is redeemed, *Offering Amount* is the issue volume of the bond in million USD, and *Coupon* its coupon rate. *IC* is the pre-tax interest coverage ratio, *IS* the ratio of operating income to sales, *DA* is the ratio of long-term debt to total assets, *DC* the ratio of total debt to total capitalization, and *BM* is the ratio of the book value of equity to its market value. *Vola* the standard deviation of daily equity returns. The variables are described in detail in Section 4. Every continuous variable is winsorized at the 0.5% and 99.5% level.

	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.95}$	Mean	Std. dev.	
Amihud (bp per mln)	0.09	0.32	0.68	1.46	4.95	1.33	1.88	
Roll (%)	0.13	0.33	0.56	0.94	2.00	0.74	0.64	
IRC (%)	0.01	0.06	0.13	0.28	0.76	0.23	0.26	
DES	0.18	0.41	0.56	0.73	0.92	0.56	0.22	
EP (*100)	-4.47	-1.18	-0.63	-0.34	-0.17	-1.15	1.60	
AQ (*100)	-3.11	-1.45	-0.88	-0.54	-0.22	-1.16	0.98	
Analyst	5	11	16	21	30	17	7	
Precision (%)	-3.15	-0.83	-0.34	-0.16	-0.06	-0.91	1.95	
FES	0.22	0.46	0.64	0.78	0.89	0.61	0.21	
Age (yr)	1.03	2.07	3.65	6.17	12.06	4.66	3.57	
Maturity (yr)	0.91	3.20	6.20	11.54	27.85	9.52	9.68	
Offer. Amt. (in mln)	150	275	425	650	1350	544	432	
Coupon (%)	2.00	5.00	6.12	7.12	8.75	5.94	1.95	
IC	1.18	3.95	6.57	11.87	26.70	9.41	9.32	
IS	0.04	0.11	0.19	0.31	0.57	0.23	0.16	
DA	0.10	0.18	0.25	0.34	0.52	0.27	0.13	
DC	0.06	0.13	0.19	0.29	0.47	0.22	0.12	
BM	0.07	0.27	0.43	0.65	1.20	0.56	0.72	
Vola	0.06	0.09	0.13	0.19	0.37	0.16	0.11	
Rating	AAA	AA	A	BBB	BB	B	CCC	CC
N	441	2202	11823	16047	5183	3327	930	59

our empirical study, separated into the illiquidity variables, the transparency variables, and the control variables. We report the mean, the standard deviation and the 5th, 25th, 50th, 75th, and 95th percentile of each variable. All illiquidity variables are defined so that larger values represent lower levels of liquidity. All transparency variables are defined so that larger values (less negative values) correspond to higher levels of transparency.[9]

[9] We choose to rescale some of the liquidity and transparency variables, relative to their standard definition in other papers, so that their magnitudes are similar. We do this to avoid having to report very small or large coefficients later on. No method that we employ is dependent on the absolute scale of a variable so this choice does not affect results.

We find considerable variation in our illiquidity measures. The mean *Amihud* illiquidity measure is 1.33 bps per \$1 million implying that a \$1 million trade moves prices of a bond bond by 0.0133 percent on average. The measure shows a very large cross-sectional variation with 5th percentile at 0.09 and the 95th percentile at 4.95 and a median value of 0.68. The *Roll* measure estimates the average bid-ask spread as 0.74% of the bond price, with values of 0.13%, 0.56%, and 2.00% at the 5th, 50th and 95 percentile respectively. The *IRC* measure estimates that the average round trip cost in percentage of the price at 0.23%. At the 5th percentile this value drops to 0.01%, whereas its 95th percentile value is 0.76% with a median value of 0.13%. These numbers show that there are significant trading costs in the bond market.

The corporate transparency measures show a similar strong variation. The *DES*, *EP*, and *AQ* proxies are, by construction, relative valuations of the company's transparency. Their numerical values are therefore difficult to interpret. The companies in our sample are well covered by analysts: The median company has 17 analysts forecasting its EPS. At the lower end, the 5th percentile is still five analysts while the 95th percentile are 30 analysts. The *Precision* measure shows that analysts agree frequently on the predicted earnings of a company. The 95 percentile value is only -0.06% with a median value of -0.34%. This means that the standard deviation of the earnings forecasts one year ahead is only 0.34% of the current stock price at the median. The average value of *Precision* is -0.91% with a standard deviation of 1.95% and a 5th percentile value of -3.15%. The distribution is therefore highly skewed with large disagreement for some companies.

The *FES* measure controls the fundamental earnings smoothing of companies. As it is a relative measure, its values are difficult to interpret. The characteristics of our bonds have reasonable variation. The average bond in our sample is 4.66 years old with a range from 1.03 (5th percentile) to 12.06 years (95th percentile). The average maturity is slightly less than 10 years with a range from 0.91 to 27.85 years. The issue amount varies from \$150 million to \$1.35 billion. These statistics are similar to other studies that have worked with the TRACE bond data (see, for example, Friewald et al. (2012)).

The credit control variables show wide dispersion reflecting the fact that our sample contains all ratings from AAA to CC. We excluded the default ratings C and D from the data. The most frequent rating is BBB, followed by A, and then BB. In total, 30,513 (76.3%) observations are from investment grade bonds (rating BBB or better) and 9,499 (23.7%) are from speculative grade bonds.

Table 2 presents the correlations between the various measures of transparency and liquidity that we employ. As is to be expected, there is moderate to strong positive correlation between the various measures of bond liquidity with values around 0.5. For the transparency measures, the picture is mixed. Most correlations are small in value (< 0.3) with the exception of the pairs *DES*-

EP, *EP-AQ* and *EP-Precision*. The magnitude of their correlation suggests that multicollinearity may affect the regression results if the variables are used as independent regressors. As discussed below, we use an aggregated measure of transparency for our main results. Hence, the large correlations are not an issue for our tests. The correlations are generally in the expected direction and all correlations are statistically significant (at the 5% level). Interestingly, DES is the only transparency variable that has negative correlations with another transparency proxy (EP).

Table 2: Correlation Matrix of Transparency and Liquidity Proxies

The table shows the correlations between the measures of firm level transparency (Panel A) and bond illiquidity (Panel B). The variables are described in Section 4. The values above the diagonal are Bravais-Pearson correlations, the values below are Spearman rank correlations. Values in bold are significant at the 5% level.

Panel A: Correlation of Transparency Proxies					
	DES	EP	AQ	Analyst	Precision
DES		**−0.306**	**0.016**	**0.121**	**0.038**
EP	**−0.326**		**0.522**	**0.084**	**0.282**
AQ	**0.050**	**0.503**		**0.253**	**0.204**
Analyst	**0.126**	**0.090**	**0.277**		**0.103**
Precision	**0.050**	**0.380**	**0.230**	**0.125**	
Panel B: Correlation of Liquidity Proxies					
	Amihud	Roll	IRC		
Amihud		**0.537**	**0.528**		
Roll	**0.604**		**0.464**		
IRC	**0.447**	**0.475**			

Both liquidity and transparency are difficult to measure empirically which is why we employ several proxies for both. The bivariate correlations suggest that the different measures do share some commonality. Hence, for parsimony, we conduct a principal component analysis (PCA) on both sets of variables as well as liquidity risk to see if the relevant information can be condensed. The results are presented in Table 3. We exclude the *DES* variable from the transparency proxies for this set because the negative correlation with *EP* makes the resulting components difficult to interpret.[10] Section 6 presents and discusses the impact of this choice.

For the transparency variables, the first PC is able to explain 45% of the variation in the data. The second PC explains an additional 23% of the variation and the third one 21%. For the illiquidity proxies, the first component is able to explain 67% of the common variation. The second PC explains an additional 18%. Finally, for the liquidity risk proxies, the first component is able to explain 64% of the common variation. The second PC explains an additional 20%. For all sets of variables, we find that the first PC loads positively on all variables and can account for a large part of the common variation. Hence, we define each first PC as an

[10]Specifically, including *DES* results in a negative loading on the first principle component. Hence, in this case, one cannot unambiguously state that if the component increases so does transparency.

Table 3: Principal component loadings

The table reports the principal component analysis loadings for each of the transparency proxies (Panel A), the illiquidity proxies (Panel B), and the liquidity risk proxies (Panel C) along with the cumulative explanatory power of the components.

Panel A: PCA loadings for Transparency Proxies				
	PC1	PC2	PC3	PC4
EP	0.59	-0.31	-0.31	0.67
AQ	0.61	0.06	-0.38	-0.69
ANALYST	0.32	0.89	0.23	0.24
PRECISION	0.41	-0.33	0.84	-0.13
Cum. % explained	0.45	0.68	0.89	1.00
Panel B: PCA loadings for Illiquidity Proxies				
	PC1	PC2	PC3	
Amihud	0.593	-0.044	-0.804	
Roll	0.571	-0.681	0.459	
IRC	0.567	0.731	0.379	
Cum. % explained	0.67	0.85	1.00	
Panel C: PCA loadings for Liquidity Risk Proxies				
	PC1	PC2	PC3	
Amihud Risk	0.604	-0.088	-0.792	
Roll Risk	0.556	0.758	0.340	
IRC Risk	0.570	-0.646	0.507	
Cum. % explained	0.64	0.84	1.00	

aggregate measure, called *Trans*, *Illiq*, and *Illiq Risk*, respectively. Since the loadings are all positive the interpretation of the measures remains valid. For transparency, for example, we can unambiguously say that a higher value for *Trans* implies that the accounting information of the company is more transparent.

5.4 Relationship between Bond Liquidity and Firm-level Transparency

In this section, we examine whether firm-level transparency influences the level of a bond's liquidity. As argued in Section 3, we expect to find a significantly lower illiquidity for bonds whose issuing firm has more transparent accounting information. As our proxies measure the illiquidity of bonds and the transparency of accounting information, we expect to find a negative relationship between these variables. The conclusions in this section are based on the entire sample of 41,661 quarter-bond observations from Q4-2004 until Q4-2012. The proxies used are described in Section 4.

To get an initial picture of the overall relationship between the two sets of variables we perform a CCA. The results are presented in Table 4. Details about the structure of the canonical variates are presented in Table C.1 in the Appendix. The first canonical correlation is 0.29

with a canonical R^2 of 0.083. Wilk's lambda strongly rejects the hypothesis that there is no correlation between the two sets of variables. In terms of absolute magnitude, however, the canonical correlation is of moderate size. These results imply that there is a statistically strong relationship between transparency and liquidity.

Table 4: Results of Canonical Correlation Analysis
The table reports the coefficients and diagnostics for the CCA of the iliquidity and transparency variables described in Section 4. Column 2 reports the canonical correlations. Wilk's lambda, reported in column 4, tests the null hypothesis that this and all following canonical correlations are equal to zero.

Canonical Function	Canonical Correlation	Canonical R^2	Wilk's Lambda	Rao's F-Approximation	P-Value
1	0.289	0.083	0.914	243.682	0.000
2	0.049	0.002	0.997	14.840	0.000
3	0.025	0.001	0.999	8.133	0.000

To test our hypotheses, we run the panel regression (2) for each of the three illiquidity proxies as well as the aggregate illiquidity measure. To conserve space, we only report the results for the aggregate liquidity and the aggregate transparency measure here. The disaggregated results for each illiquidity proxy can be found in Appendix D. The disaggregated results are qualitatively the same as for the aggregate measures, although the coefficients are not always statistically significant for all transparency measures simultaneously. This is a result of the multicollinearity, especially between AQ and EP.

The results of the regressions are presented in Table 5. For comparison, we first report the results of the regression including only the bond characteristics and fixed effects (model (1)). As expected, illiquidity of a bond increases with its age. The R^2 of the regression is 0.21 showing that the fixed effects (which subsume bond characteristics and time variation) and age can explain much of the variation in illiquidity of bonds. Next, we add the measure of accounting transparency. Model (2) shows that there is a strong relationship between transparency and illiquidity in the bond market. As expected, the relationship is negative implying that higher levels of transparency is associated with higher levels of liquidity on the bond market. Quantitatively, a one standard deviation increase of *Trans* decreases *Illiq* by 0.130, which is a 29.9 percent of the median value of *Illiq*.

We also find strong support for our second hypothesis that the relationship between transparency and illiquidity should be non-linear: The quadratic term in model (3) highly significant. The quadratic coefficient is negative, so the relationship is globally concave and inverse U-shaped. The range of the transparency measure is such that the relationship is decreasing for all bonds. This implies that liquidity increases overproportionally as firms become more transparent. In the quadratic specification, a one standard deviation increase of the *Trans* measure from its

Table 5: Illiquidity Transparency Panel Regressions

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's illiquidity:

$$\text{Illiquidity}_{i,t} = a_1\ \text{Trans}_{i,t-1} + a_2\ \text{Trans}^2_{i,t-1} + \mathbf{b}\cdot\text{Bond Controls}_{i,t-1} + \mathbf{c}\cdot\text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

The first three columns contain results without credit risk controls. In Regression (1), we report the results for only the bond characteristics. Regression (2) includes transparency while Regression (3) additionally includes the quadratic transparency variable. Regression (4) contains the bond characteristics as well as the credit risk controls. Finally, the last two columns contain the all three sets of variables. Regression (5) contains transparency while Regression (6) includes an additional quadratic transparency variable. The variables are described in Section 4 and the data set in Section 5.3. Each model is estimated using two-way fixed effects using the within estimator. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2.

	(1)	(2)	(3)	(4)	(5)	(6)
Trans		-0.098***	-0.142***		-0.069***	-0.108***
		(-5.29)	(-5.23)		(-4.41)	(-4.75)
Trans^2			-0.012**			-0.010**
			(-2.46)			(-2.30)
Age	0.061***	0.061***	0.060***	0.062***	0.062***	0.061***
	(5.99)	(6.10)	(6.06)	(6.47)	(6.43)	(6.38)
IC5				-0.057***	-0.048***	-0.048***
				(-4.29)	(-3.73)	(-3.77)
IC10				0.002	0.003	0.005
				(0.28)	(0.46)	(0.68)
IC20				-0.001	-0.001	-0.001
				(-0.18)	(-0.26)	(-0.26)
IC30				0.001	0.001	0.001
				(0.62)	(0.54)	(0.51)
IS				-0.123	-0.094	-0.091
				(-1.15)	(-0.90)	(-0.87)
DA				0.440**	0.312	0.302
				(1.97)	(1.42)	(1.41)
DC				-0.191	-0.207	-0.223
				(-0.71)	(-0.77)	(-0.83)
BM				0.046	0.038	0.034
				(0.96)	(0.80)	(0.72)
Vola				0.872***	0.752***	0.742***
				(5.35)	(4.84)	(4.92)
R^2	0.2108	0.2265	0.2288	0.2294	0.2351	0.2368

$*p < 0.1, **p < 0.05, ***p < 0.01$

median value decreases *Illiq* by 0.22, which represents a change of 50.7 percent of its median value. This effect is about twice as large as in the linear specification and about the change in illiquidity as an increase in age of 3.5 years.

As described in Section 2, many prior studies have documented a close relationship between the credit risk of a bond and its liquidity. Models (4) through (6) therefore report the regression results with several controls for credit risk. Model (4) contains only the bond characteristics and the credit risk controls. We find that most proxies are insignificant. Interest coverage (IC) is negatively related to illiquidity, while the debt to asset ratio (DA) is positively related. Both coefficients indicate that higher credit risk is associated with lower liquidity. The negative estimate of the debt to capital ratio (DC) is due to the fact that it is highly correlated with DA (the correlation coefficient is 0.75). The results also show that higher equity volatility increases illiquidity. Following the logic of structural models of credit risk, and assuming that higher equity volatility implies higher asset volatility, the likelihood of default increases as equity becomes riskier. The other ratios are insignificant.

Including transparency in the regression (model (5)), changes the estimated parameters only slightly (relative to models (4) and (2)). The coefficient for *Trans* remains negative and highly significant. The same can be said for the quadratic specification including credit controls (model (6)) compared to model (3). Hence, it seems that transparency impacts illiquidity by itself independent of credit risk. Quantitatively, in model (5), a one standard deviation increase of *Trans* decreases *Illiq* by 0.091, which is a 21.0 percent increase relative to its median value. In model (6), a one standard deviation increase of the *Trans* measure from its median value decreases *Illiq* by 0.17, which represents a change of 39.1 percent of its median value. When all credit risk ratios change by one standard deviation in the direction of higher liquidity, the decrease in *Illiq* is 0.066 (15.2 percent of median) and 0.065 (15.0 percent of median) in models (5) and (6), respectively.

Comparing the R^2s of the models, we find that transparency increases the fit by 7.2% in relative terms compared to the base case in model (1) (including the quadratic term, the increase is 8.7%) while credit risk increases the fit by 8.5%. The increase in R^2 from including transparency in the model with credit risk (4) is still 2.5% (3.5% with the quadratic term). This suggests that the effect of accounting transparency is equally important in explaining the variation in bond liquidity as is credit risk. Also, transparency has incremental explanatory power for liquidity independent of credit risk.

The results in this section clearly show that transparency has an economically significant effect on bond liquidity. As bonds trade with liquidity premia, these results imply that accounting transparency has a direct impact on the cost of capital of firms.

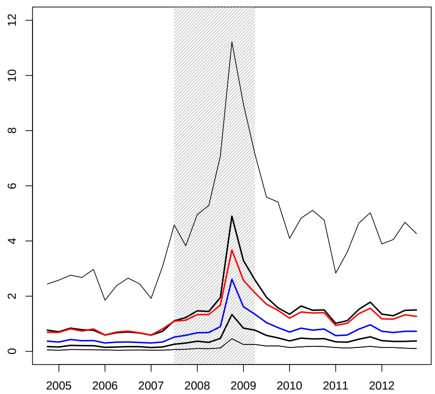
5.5 Relationship between Bond Liquidity and Firm-level Transparency in Times of Financial Distress

In this section, we explore if and how the relationship between bond liquidity and firm transparency depends on financial distress. As argued in Section 3, we expect the importance of transparency to increase during times of distress. We measure financial distress in four different ways.

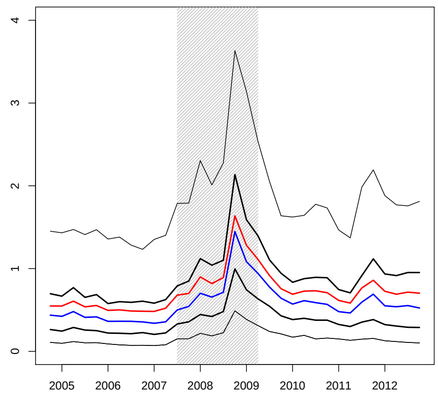
The recent financial crisis has had a profound impact on the liquidity of bond markets (see, e.g., Dick-Nielsen et al. (2012) and Friewald et al. (2012)). Hence, to test if and how the relationship between transparency and bond liquidity is affected by aggregate changes in bond

Figure 1: Time Series Plots of Liquidity Proxies

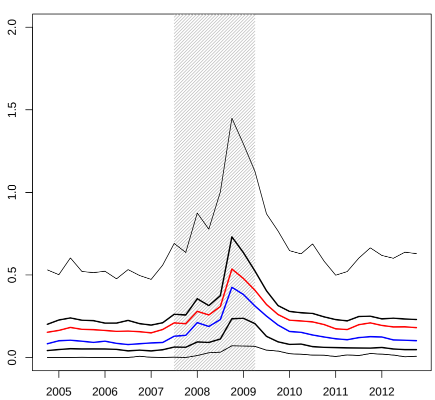
The figure presents the time series plots of the liquidity proxies described in Section 4 from Q4 2004 until Q4 2012. The gray-shaded area represents the time period from Q3 2007 until Q4 2009 which we consider to be the Crisis period. The mean value is plotted in red, the median in blue. The other lines represent the 5th, 25th 75th and 95th percentile.



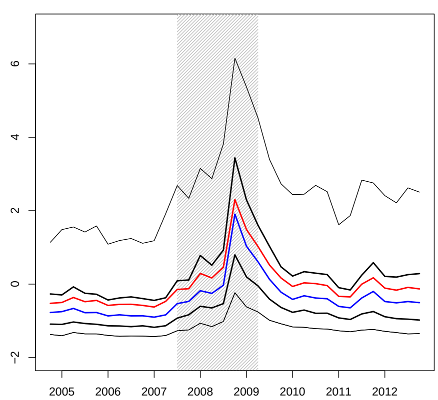
(a) Amihud



(b) Roll



(c) IRC



(d) Illiq

market liquidity, we split our sample into two subperiods: Normal and Crisis. The Crisis period is taken to be from Q3 2007 to Q2 2009. Figure 1 presents time series plots of our illiquidity proxies. The strong effect of the crisis can be clearly seen. The *Amihud*, *Roll*, and *IRC* measures all exhibit a several standard deviations large spike around the Lehman Brothers collapse. The results for the two subperiods are presented in Panel A of Table 6. To conserve space, we only report the coefficients for the transparency variable. We find that the relationship between transparency and bond illiquidity is robust over the different time periods and that the non-linearity is measurable in both. For both periods, the estimated coefficients are negative and significant. Quantitatively, we find that the estimated coefficient is about twice as large during the Crisis as in normal times. These results indicate that transparency plays a larger role in determining the cross-sectional differences during the crisis. However, the change in coefficients cannot be used to test whether the impact of transparency is indeed larger during the crisis as the independent variables change themselves.

To test whether transparency has a larger impact during the crisis we include a dummy interaction term of the *Trans* proxy and a dummy for the Crisis period in the regression. The results for this regression is presented in Panel B of Table 6. As expected we find that the interaction variable is significant. To provide further evidence that transparency has a larger impact during the crisis, we split our data sample into transparent and intransparent companies. A company is deemed transparent if its average quarterly *Trans* proxy is above the total average of all firms and intransparent if its average value is below. We find that for transparent firms, the crisis does not have an additional effect on the relationship between transparency and bond liquidity whereas it does so for intransparent firms. During the crisis, the impact of transparency on bond liquidity for opaque firms is about three times as large as during normal times.[11]

In order to measure liquidity dry-ups on a bond level, we define that a bond is experiencing a sudden liquidity withdrawal if the quarterly estimate of illiquidity is more than two standard deviations above its median value. These are quarters during which a bond is suddenly traded with much lower levels of liquidity. Table 7 reports the results in an analogous fashion as before for the financial crisis. We find that the coefficients for *Trans* increase in absolute value during liquidity dry-ups, both in the linear and quadratic specification. The dummy interaction term (column five) shows that the impact of transparency is indeed larger during a liquidity dry-up.

To measure distress on a company level, we use its credit rating. Our sample contains bonds with ratings from AAA to CC. If our hypothesis is correct, the impact of transparency for low-grade bonds on liquidity should be larger than on investment grade bonds. At the same time, there is also evidence that accounting transparency has an impact on credit ratings (Ashbaugh-Skaife et al., 2006). It is well known that credit ratings are only an imperfect measure of a bonds credit risk. We are mainly concerned with measuring the likelihood of financial distress. We therefore use a bond's expected default frequency (EDF) as a measure of the likelihood of default (see Bharath and Shumway (2008) and Vassalou and Xing (2004) for details). This measure is a direct measure of the likelihood of default and may be more appropriate to measure financial distress.

The results for the different bond ratings are presented in Panel B of Table 8. To ensure that sufficient observations are available for each rating, we group the ratings AAA and AA as

[11]Although the magnitude of the coefficient for transparent firms (-0.117) is larger than for opaque firms (-0.035), we estimate the standardized coefficients for transparent firms as -0.064 while it is -0.05355 for opaque firms. This shows that in normal times, the impact of transparency is about equal among all firms.

Table 6: Liquidity Transparency Regressions in Financial Crisis

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = a_1 \text{ Trans}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

Panel A contains the results for the normal period and the crisis period (2007Q3 - 2009Q3). For each period, model (1) contains only a linear transparency term while model (2) contains an additional quadratic term. Panel B contains the results including an interaction term of *Trans* with a dummy indicator. Column 1 is based on the full sample, column 2 is based only on firms with an average transparency above the overall average among all firms while column 3 is based on firms with an average transparency below the overall average. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2. To conserve space, only the coefficients for the transparency variables are reported.

Panel A: Time Periods				
	Normal(1)	Crisis(1)	Normal(2)	Crisis(2)
Trans	-0.058***	-0.112***	-0.092***	-0.167***
	(-4.32)	(-3.15)	(-4.16)	(-3.93)
Trans^2			-0.009**	-0.013*
			(-2.07)	(-1.96)
N	31370	8642	31370	8642
R^2	0.1440	0.2511	0.1467	0.2519

Panel B: Dummy Interaction			
	Full Sample	Transparent Firms	Intransparent Firms
Trans	-0.058***	-0.117***	-0.035**
	(-4.12)	(-4.18)	(-2.14)
Trans × Crisis Dummy	-0.058**	-0.075	-0.076**
	(-2.12)	(-0.86)	(-2.53)
N	40012	21401	18611
R^2	0.2359	0.2237	0.2387

$*p < 0.1, **p < 0.05, ***p < 0.01$

well as CCC and CC together. As expected, we find that the impact of transparency on bond liquidity is larger for lower rated bonds than for higher rated bonds. For bonds rated A and above no significant effect is found (the estimated coefficients are negative though). For all other categories, we find a significant negative effect. The largest coefficient was found for the lowest rating category. The coefficient for BBB rated bonds is surprisingly large compared to the other rating categories.

Finally, the results for the different EDF categories are presented in Panel C of Table 8. We define three categories of EDF as follows: The low EDF category is for bonds with values below 0.00001, the medium EDF category is for bonds with values between 0.00001 and 0.1, and the high EDF category for bonds with values above 0.1. As expected, we find that the coefficient of transparency to increase (in absolute value) as EDF increases. This suggests that as the likelihood of near-term default increases, bond trading becomes more information sensitive in the sense that for less transparent companies liquidity decreases more severely than for companies

Table 7: Liquidity Transparency Regressions in Liquidity Dry-ups

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = a_1 \text{ Trans}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

Columns 1 to 4 contain the results for normal periods and periods of liquidity dry-ups. A quarter with a liquidity dry-up is defined to be one where the illiquidity of a bond is more that two standard deviations larger than its median value. For each period, model (1) contains only a linear transparency term while model (2) contains an additional quadratic term. Column 5 contains the results including an interaction term of *Trans* with a dummy indicator for liquidity dry-ups. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2. To conserve space, only the coefficients for the transparency variables are reported.

	Normal(1)	Dry-up(1)	Normal(2)	Dry-up(2)	Dummy Interaction
Trans	-0.060***	-0.097**	-0.084***	-0.215***	-0.095***
	(-4.79)	(-2.42)	(-4.66)	(-3.50)	(-4.74)
Trans^2			-0.006*	-0.030***	-0.011**
			(-1.75)	(-3.28)	(-2.54)
Trans × Dry-up Dummy					-0.193**
					(-2.23)
N	37198	2814	37198	2814	40012
R^2	0.1831	0.2242	0.1849	0.2266	0.2383

$*p < 0.1, **p < 0.05, ***p < 0.01$

with transparent accounting information.

5.6 Relationship between Bond Liquidity Uncertainty and Firm-level Transparency

To examine the relationship between the liquidity risk of corporate bonds and firm-level transparency we use a similar empirical strategy as before. We use the same regression equation as before but with liquidity risk as independent variable:

$$\begin{aligned}\text{Liquidity Risk}_{i,t} = a \text{ Trans}_{i,t-1} + \mathbf{b} \cdot \text{Bond Characteristics}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.\end{aligned} \quad (3)$$

As described in Section 4, we use the variability of the illiquidity proxies as measures of liquidity risk. We hypothesized that higher levels of transparency should lead to lower levels of liquidity risk. Hence, we expect the regression coefficients to be negative. We use the same set of controls for bond characteristics and credit risk. As several studies have emphasized the impact of the financial crisis on liquidity risk of bonds (see, for example, Friewald et al. (2012) and Dick-Nielsen et al. (2012)), we also report results for the different subperiods as described in the previous section. Again, we only report the results for the aggregate measures of transparency (*Trans*) and liquidity risk (*Illiq Risk*). The complete results are presented in Appendix E.

Table 8: Liquidity Transparency Regressions in Financial Distress

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = a_1 \text{ Trans}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

Panel A contains the results separated by ratings. Panel B contains the results separated by expected default frequency (EDF), where low is less than 0.0001, medium is between 0.0001 and 0.1, and high is above 0.1. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2. To conserve space, only the coefficients for the transparency variables are reported.

Panel A: Credit Rating of Bond						
	AAA-AA	A	BBB	BB	B	CCC-CC
Trans	-0.019	-0.051	-0.105***	-0.046**	-0.050*	-0.136***
	(-0.35)	(-1.47)	(-3.23)	(-2.37)	(-1.70)	(-3.82)
N	2643	11823	16047	5183	2984	989
R^2	0.2078	0.2365	0.2524	0.2097	0.3273	0.3594
Panel B: Expected Default Frequency (EDF) of Bond						
	Low EDF	Medium EDF	High EDF			
Trans	-0.061***	-0.190***	-0.209***			
	(-4.45)	(-3.19)	(-4.23)			
N	34742	4018	1252			
R^2	0.1763	0.3197	0.3604			

$*p < 0.1, **p < 0.05, ***p < 0.01$

The results, presented in Table 9, clearly confirm our hypothesis. In all regressions is the estimated coefficient of the *Trans* measure negative and significant. The first column reports the results of the regression without a measure of transparency and without the credit risk controls. The overall R^2 of this regression is 17.22% showing that much of the cross-sectional variation in liquidity risk is captured by the fixed-effects and bond characteristics. Column two contains the credit risk controls. The overall R^2 in this regression is 19.69% which represents an improvement of 14.3% on a relative basis. This confirms the results of Dick-Nielsen et al. (2012) and Friewald et al. (2012) that liquidity risk and credit risk are impacted by one another. In particular, interest coverage (*IC*), profitability (*IS*), leverage (*DA*), and equity volatility (*Vola*) show a significant impact on liquidity risk. Column three reports the results for the full sample and including transparency. The improvement in R^2 compared to model (2) is 2.7%. As expected, the estimated effect is negative suggesting that transparent accounting information reduced liquidity risk. Quantitatively, a one standard deviation increase of *Trans* decreases *Illiq Risk* by 0.126, which is a 33.5 percent increase relative to its median value.

The results for the different time periods are reported in columns four (Normal times) and five (Crisis). We find that the impact of transparency on liquidity risk is much larger during the crisis. These results are confirmed by the interaction term of *Trans* with the crisis dummy

Table 9: Liquidity Risk Transparency Regressions

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's illiquidity:

$$\text{Liquidity Risk}_{i,t} = a\ \text{Trans}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

The first three columns contain the results for the full sample. Column 1 contains the results using only fixed effects and bond controls, column 2 are the results including bond controls and credit risk, and column 3 are the results for the full specification. Column 4 and 5 are based on the sub-samples for normal times and the financial crisis (2007Q3-2009Q2). The variables are described in Section 4 and the data set in Section 5.3. Each model is estimated using two-way fixed effects using the within estimator. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2.

Panel A: Full Sample Regressions

	Bond Controls	Credit Risk	Transparency	Normal	Crisis
Trans			-0.095***	-0.083***	-0.146***
			(-4.75)	(-5.12)	(-2.75)
Age	0.016*	0.018**	0.017**	0.026***	0.012
	(1.90)	(2.29)	(2.19)	(4.20)	(1.01)
IC5		-0.056***	-0.046***	-0.049***	-0.034
		(-4.43)	(-4.00)	(-4.14)	(-1.52)
IC10		0.006	0.008	0.009	0.002
		(0.79)	(1.18)	(1.23)	(0.09)
IC20		0.001	0.001	-0.002	0.003
		(0.32)	(0.16)	(-0.45)	(0.42)
IC30		0.002	0.002	0.003**	0.000
		(1.28)	(1.14)	(2.19)	(0.05)
IS		-0.206**	-0.170**	-0.120	-0.395***
		(-2.28)	(-1.97)	(-1.29)	(-2.68)
DA		0.677***	0.529**	0.346	0.598
		(2.72)	(2.16)	(1.35)	(1.30)
DC		-0.114	-0.125	0.058	-0.429
		(-0.39)	(-0.43)	(0.19)	(-0.86)
BM		0.070	0.058	-0.005	0.061
		(1.35)	(1.14)	(-0.10)	(1.25)
Vola		1.084***	0.933***	0.610***	1.477***
		(4.86)	(4.50)	(4.23)	(4.00)
R^2	0.1722	0.1969	0.2023	0.0861	0.2460

Panel B: Interaction Dummy Regressions

	Full Sample	Transparent Firms	Opaque Firms
Trans	-0.054***	-0.075***	-0.042***
	(-4.30)	(-2.94)	(-2.98)
Trans × Crisis Dummy	-0.094***	-0.088	-0.102***
	(-3.08)	(-1.06)	(-2.87)
N	40012	21401	18611
R^2	0.2035	0.1792	0.2152

$*p < 0.1, **p < 0.05, ***p < 0.01$

in Panel B. Overall, the impact of transparency on liquidity risk during the crisis is about three times as large as during normal times. Similar to the results for the level of liquidity, we find that this result only applies to firms that are generally opaque (i.e. firms with an average transparency below the global average). We find that for transparent firms, the crisis does not have an additional effect on the relationship between transparency and liquidity risk. For opaque firms, the impact of transparency on bond liquidity risk is more than three times as large as during normal times.[12]

6 Robustness Checks

The initial results suggest that there is a strong relationship between bond liquidity and transparency of accounting information. Moreover, our results indicate that this relationship is non-linear. In this section, we provide further evidence that our measured effects are robust and economically meaningful.

A potential explanation of the impact of transparency on bond liquidity is that transparency is related to bond characteristics. Firms with a higher transparency proxy may simply be companies that have issued bonds with a higher coupon, a larger issue size, or a shorter maturity. Each of these characteristics is generally associated with higher levels of liquidity. In addition, it is well documented that accounting transparency affects equity returns and volatility (see, for example, Stoll (2000) and (Easley et al., 2002)). As far as equity returns and volatility have an impact on bond liquidity, this mechanism may be responsible for the large effect of transparency. To address these concerns, we reestimate model (2) including interaction terms between the bond characteristics and the transparency proxy. In addition, we include return on equity (RoE), measured as the annualized average daily return of a company's stock in a quarter, to the set of controls as well as interaction terms between transparency and return and volatility of equity. Table 10 reports the results including the relevant interaction terms.

We find that the inclusion of the interaction terms does not alter the results. The bond characteristics have no measurable influence on the relationship between transparency and bond liquidity. Each interaction term is insignificant. We find no influence of equity returns on bond liquidity directly, but we do find that the interaction term of transparency with return on equity is positive and significant indicating that when equity returns are high transparency has a smaller impact on bond liquidity. Finally, the interaction term with equity volatility is significant and negative indicating that when equity is riskier transparency has a larger impact on bond liquidity.

Our primary results are based on a one-quarter lag. It is conceivable that the true effects of accounting information transparency are not immediately reflected in trading of investors. To test for this possibility, we report the results of the panel regression including lags up to order four of the transparency measures. We report results without controls in Table 11 and with controls in Table 12. The main results are not affected by the addition of higher lags.

[12] Although the magnitude of the coefficient for transparent firms (-0.075) is larger than for opaque firms (-0.042), the standardized coefficients for transparent firms is -0.04 while it is -0.064 for opaque firms. This shows that in normal times, the impact of transparency is larger for opaque firms.

Table 10: Liquidity Transparency Regressions with Interaction Effects

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\begin{aligned}\text{Illiquidity}_{i,t} = {} & a_1 \text{Trans}_{i,t-1} + a_2 \text{Trans}^2_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} \\ & + \mathbf{d} \cdot \text{Trans}_{i,t-1} \times \text{Interaction Variables}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}\end{aligned}$$

Column (1) add return on equity (*RoE*) to the regression specification. Column (2) and (3) report the results when interaction terms of transparency with equity and bond characteristics are included, respectively. Column (4) are the results for the complete model. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis.

	(1)	(2)	(3)	(4)
Trans	-0.108***	-0.083***	-0.142***	-0.120**
	(-4.76)	(-3.46)	(-2.89)	(-2.46)
Trans^2	-0.010**	-0.015***	-0.012**	-0.016***
	(-2.29)	(-3.75)	(-2.56)	(-3.88)
Age	0.061***	0.061***	0.061***	0.061***
	(6.37)	(6.38)	(6.31)	(6.30)
IC5	-0.048***	-0.043***	-0.049***	-0.044***
	(-3.77)	(-3.23)	(-3.76)	(-3.24)
IC10	0.005	0.002	0.005	0.003
	(0.70)	(0.33)	(0.67)	(0.34)
IC20	-0.001	-0.002	-0.001	-0.002
	(-0.24)	(-0.31)	(-0.27)	(-0.31)
IC30	0.001	0.001	0.001	0.001
	(0.51)	(0.48)	(0.49)	(0.47)
IS	-0.092	-0.055	-0.094	-0.058
	(-0.88)	(-0.54)	(-0.90)	(-0.58)
DA	0.294	0.274	0.303	0.274
	(1.37)	(1.26)	(1.41)	(1.26)
DC	-0.208	-0.228	-0.254	-0.257
	(-0.77)	(-0.83)	(-0.94)	(-0.92)
BM	0.035	0.015	0.032	0.013
	(0.74)	(0.34)	(0.67)	(0.30)
Vola	0.758***	0.680***	0.739***	0.680***
	(5.18)	(5.34)	(4.87)	(5.29)
RoE	0.036	0.100		0.099
	(0.57)	(1.48)		(1.45)
Trans × Vola		-0.186***		-0.183***
		(-3.79)		(-3.63)
Trans × RoE		0.091***		0.093***
		(4.00)		(4.03)
Trans × Maturity			0.005	0.005
			(1.43)	(1.42)
Trans × Coupon			-0.000	0.001
			(-0.08)	(0.09)
Trans × log(Off.Amt.)			-0.000	-0.000
			(-0.95)	(-1.12)
R^2	0.2368	0.2388	0.2431	0.2450

$*p < 0.1, **p < 0.05, ***p < 0.01$

Interestingly, we find that the coefficients at the third lag are significant, both the linear and quadratic term and in both the specification with and without controls. This results is consistent for each measure of illiquidity.

Table 11: Liquidity Transparency Regressions with lags without Controls

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = \sum_{j=1}^{4} a_{1,j}\text{Trans}_{i,t-j} + \sum_{j=1}^{4} a_{2,j}\text{Trans}^2_{i,t-j} + \alpha_i + \delta_t.$$

Each column contains the results for the illiquidity measure indicated at the top, either using only the linear terms (model (1)) or also including the quadratic terms (model (2)) of the transparency measure. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
Trans_{t-1}	-0.110***	-0.107**	-0.021***	-0.033***	-0.036***	-0.030***	-0.127***	-0.126***
	(-2.78)	(-2.55)	(-2.84)	(-2.80)	(-3.41)	(-3.64)	(-3.39)	(-3.25)
Trans_{t-2}	0.031	0.003	0.013	0.032	0.016*	0.011	0.056	0.054
	(0.77)	(0.05)	(1.25)	(1.53)	(1.81)	(1.57)	(1.46)	(1.22)
Trans_{t-3}	-0.006	-0.054*	-0.016	-0.035**	-0.001	-0.012*	-0.018	-0.073***
	(-0.32)	(-1.81)	(-1.54)	(-2.49)	(-0.15)	(-1.70)	(-1.02)	(-2.72)
Trans_{t-4}	-0.014	-0.044	-0.003	-0.010	-0.002	-0.006	-0.009	-0.036*
	(-1.08)	(-1.46)	(-0.38)	(-1.38)	(-0.39)	(-1.13)	(-0.76)	(-1.80)
Trans^2_{t-1}		-0.001		-0.004		0.001		-0.001
		(-0.20)		(-1.62)		(1.05)		(-0.14)
Trans^2_{t-2}		-0.007		0.005		-0.001		-0.000
		(-1.35)		(1.37)		(-1.29)		(-0.07)
Trans^2_{t-3}		-0.011***		-0.005***		-0.003***		-0.013***
		(-5.23)		(-2.99)		(-2.71)		(-4.33)
Trans^2_{t-4}		-0.012**		-0.002		-0.002**		-0.009***
		(-1.98)		(-1.44)		(-2.22)		(-2.69)
R^2	0.11	0.11	0.13	0.13	0.14	0.15	0.18	0.19

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 12: Liquidity Transparency Regressions with lags with Controls

The table reports the results of the panel data regression model to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = \sum_{j=1}^{4} a_{1,j}\text{Trans}_{i,t-j} + \sum_{j=1}^{4} a_{2,j}\text{Trans}^2_{i,t-j} + \mathbf{b}\cdot\text{Bond Controls}_{i,t-1} + \mathbf{c}\cdot\text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t.$$

Each column contains the results for the illiquidity measure indicated at the top, either using only the linear terms (model (1)) or also including the quadratic terms (model (2)) of the transparency measure. Only the coefficients for the lagged transparency variable are reported. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
Trans_{t-1}	-0.079**	-0.078**	-0.016**	-0.030**	-0.026***	-0.020***	-0.094***	-0.094***
	(-2.42)	(-2.20)	(-2.25)	(-2.51)	(-3.48)	(-3.10)	(-3.19)	(-2.84)
Trans_{t-2}	0.031	0.008	0.015	0.034*	0.016**	0.011*	0.056*	0.058
	(0.88)	(0.17)	(1.47)	(1.74)	(2.23)	(1.92)	(1.78)	(1.52)
Trans_{t-3}	-0.013	-0.055**	-0.016	-0.034**	-0.003	-0.013**	-0.025*	-0.075***
	(-0.82)	(-2.15)	(-1.51)	(-2.46)	(-0.68)	(-2.11)	(-1.77)	(-3.16)
Trans_{t-4}	-0.015	-0.041	-0.003	-0.010	-0.002	-0.006	-0.011	-0.036**
	(-1.40)	(-1.56)	(-0.38)	(-1.45)	(-0.66)	(-1.32)	(-1.05)	(-2.15)
Trans^2_{t-1}		-0.001		-0.004*		0.002		-0.000
		(-0.11)		(-1.68)		(1.22)		(-0.07)
Trans^2_{t-2}		-0.006		0.005		-0.001		0.001
		(-1.09)		(1.45)		(-1.21)		(0.13)
Trans^2_{t-3}		-0.010***		-0.005***		-0.002**		-0.012***
		(-4.49)		(-2.93)		(-2.43)		(-3.74)
Trans^2_{t-4}		-0.010*		-0.002		-0.001*		-0.009**
		(-1.84)		(-1.42)		(-1.84)		(-2.43)
Age	0.108***	0.107***	0.009**	0.009**	0.009***	0.009***	0.061***	0.060***
	(8.40)	(8.39)	(2.52)	(2.45)	(6.91)	(6.80)	(6.39)	(6.31)
IC5_{t-1}	-0.043**	-0.043**	-0.014***	-0.014***	-0.011***	-0.011***	-0.047***	-0.046***
	(-2.54)	(-2.54)	(-3.05)	(-3.10)	(-4.05)	(-3.97)	(-3.46)	(-3.45)
IC10_{t-1}	0.007	0.009	-0.000	0.000	0.001	0.001	0.003	0.004
	(0.62)	(0.78)	(-0.03)	(0.10)	(0.48)	(0.56)	(0.45)	(0.58)
IC20_{t-1}	-0.011	-0.011	-0.000	-0.000	0.000	0.001	-0.004	-0.003
	(-1.31)	(-1.28)	(-0.13)	(-0.10)	(0.56)	(0.61)	(-0.63)	(-0.56)
IC30_{t-1}	0.002	0.002	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.68)	(0.60)	(-0.26)	(-0.31)	(-0.34)	(-0.41)	(0.20)	(0.14)
IS_{t-1}	-0.266**	-0.255**	0.025	0.027	-0.044**	-0.043**	-0.130	-0.123
	(-2.16)	(-2.13)	(0.73)	(0.78)	(-2.09)	(-2.06)	(-1.27)	(-1.22)
DA_{t-1}	0.283	0.224	0.217*	0.213*	0.006	-0.002	0.296	0.264
	(0.64)	(0.52)	(1.80)	(1.79)	(0.16)	(-0.06)	(1.13)	(1.04)
DC_{t-1}	-0.602	-0.586	-0.213	-0.219	0.062	0.065	-0.211	-0.215
	(-1.27)	(-1.25)	(-1.37)	(-1.41)	(1.30)	(1.40)	(-0.69)	(-0.72)
BM_{t-1}	0.032	0.019	-0.008	-0.010	0.005	0.004	0.032	0.023
	(0.60)	(0.36)	(-0.53)	(-0.65)	(0.56)	(0.38)	(0.65)	(0.47)
Vola_{t-1}	0.558***	0.506***	0.143***	0.136***	0.202***	0.195***	0.721***	0.686***
	(3.71)	(3.56)	(2.83)	(2.70)	(4.23)	(4.23)	(5.05)	(5.11)
R^2	0.17	0.17	0.14	0.14	0.18	0.19	0.23	0.23

$*p < 0.1, **p < 0.05, ***p < 0.01$

A possible explanation for the nonlinearity might be that, in general, each firm in our sample has multiple bonds outstanding at any point in time. With the exception of the age variable, all of our control variables and in particular our transparency measure are observed at the firm level. We therefore select one bond per company using the following procedure: For each firm, we select the bonds with the largest issue size. If multiple bonds qualify, we take the bonds that have the most recent offering date. If there are still multiple bonds, we take the bond with the shortest time to maturity. In each case, we select a criterion that should increase the liquidity of the bond chosen.[13] This way we obtain a unique bond for each of the 695 firms in the sample with a total of 7606 quarterly observations. The results are reported in Tables 13 and 14. We find little change to the original complete results for each measure of illiquidity.

Table 13: Liquidity Transparency Regressions without Controls (one Bond per Company)
The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\begin{aligned}\text{Illiquidity}_{i,t} = {} & a_1 \text{Trans}_{i,t-1} + a_2 \text{Trans}^2_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} \\ & + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.\end{aligned}$$

The variables are described in Section 4 and the data set in Section 5.3. The regression is run using only one bond per company in the sample. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
Trans	-0.036	-0.112***	-0.003	-0.026*	-0.017***	-0.032***	-0.048**	-0.128***
	(-1.31)	(-2.75)	(-0.42)	(-1.94)	(-4.05)	(-5.58)	(-2.39)	(-4.33)
Trans^2		-0.018**		-0.005**		-0.004***		-0.018***
		(-1.99)		(-2.28)		(-2.90)		(-2.88)
R^2	0.10	0.10	0.09	0.09	0.14	0.14	0.16	0.16

$*p < 0.1, **p < 0.05, ***p < 0.01$

7 Conclusion

The purpose of this paper is to explore the relationship between corporate transparency and bond liquidity. In the theoretical literature, there is general agreement that the adverse selection created by asymmetric information is a major cause of market illiquidity. To the extent that transparent accounting information can mitigate asymmetric information and provide credible signals to investors about the prospects of a company there should be a negative relationship between measures of corporate transparency and illiquidity on financial markets.

Prior research has focused exclusively on the impact of disclosure quality and accounting transparency on stock market liquidity and liquidity risk. The empirical literature is in agreement that corporate transparency has a positive effect on the level of liquidity of stocks (Welker (1995); Leuz and Verrecchia (2000); Lang et al. (2012)) and lowers the impact of liquidity risk (Lang and Maffett (2011); Ng (2011)). No prior study has yet analyzed the relationship for the bond

[13] We have experimented with the selection procedure and obtained similar results in each base. For one, we have reversed the selection criterion thereby choosing the presumably least liquid bond for each firm. We have also used the medium value for each bond characteristic. Finally, we have used random selection.

Table 14: Liquidity Transparency Regressions with Controls (one Bond per Company)
The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = a_1 \text{Trans}_{i,t-1} + a_2 \text{Trans}^2_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

The variables are described in Section 4 and the data set in Section 5.3. The regression is run using only one bond per company in the sample. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
Trans	-0.005	-0.061*	0.000	-0.023*	-0.009***	-0.022***	-0.020	-0.094***
	(-0.27)	(-1.74)	(0.01)	(-1.78)	(-4.00)	(-5.01)	(-1.41)	(-3.62)
Trans^2		-0.013		-0.005**		-0.003***		-0.017***
		(-1.57)		(-2.35)		(-2.71)		(-2.80)
Age	0.141***	0.141***	0.012*	0.012*	0.008***	0.008***	0.073***	0.073***
	(9.07)	(9.09)	(1.89)	(1.91)	(3.93)	(3.96)	(5.33)	(5.39)
IC5	-0.048**	-0.048**	-0.009	-0.009	-0.009***	-0.009***	-0.040***	-0.040***
	(-2.09)	(-2.10)	(-1.00)	(-1.01)	(-3.07)	(-3.08)	(-2.64)	(-2.66)
IC10	0.032	0.033	0.013**	0.014**	0.004*	0.004**	0.031**	0.032***
	(1.56)	(1.61)	(2.38)	(2.44)	(1.93)	(2.06)	(2.51)	(2.64)
IC20	-0.017	-0.017	0.000	0.000	0.001	0.001	-0.002	-0.002
	(-1.22)	(-1.22)	(0.03)	(0.05)	(0.96)	(0.97)	(-0.23)	(-0.21)
IC30	0.004	0.004	0.001	0.001	-0.000	-0.000	0.001	0.001
	(1.08)	(1.07)	(0.92)	(0.92)	(-0.93)	(-0.96)	(0.57)	(0.56)
IS	-0.092	-0.084	0.021	0.019	-0.057**	-0.056**	-0.105	-0.106
	(-0.47)	(-0.43)	(0.29)	(0.27)	(-2.08)	(-2.00)	(-0.71)	(-0.71)
DA	1.018**	1.010**	0.372**	0.373**	0.096	0.094	0.987***	0.988***
	(2.12)	(2.10)	(2.14)	(2.14)	(1.58)	(1.53)	(2.62)	(2.59)
DC	-0.962	-0.988	-0.311	-0.324*	0.001	-0.005	-0.651	-0.692
	(-1.55)	(-1.57)	(-1.64)	(-1.69)	(0.01)	(-0.06)	(-1.39)	(-1.45)
BM	0.166**	0.165**	0.025	0.025	0.018*	0.018*	0.153***	0.154***
	(2.56)	(2.49)	(0.85)	(0.85)	(1.89)	(1.78)	(2.77)	(2.70)
Vola	1.336***	1.311***	0.242***	0.236**	0.282***	0.276***	1.214***	1.192***
	(4.60)	(4.50)	(2.58)	(2.52)	(3.62)	(3.58)	(3.93)	(3.90)
R^2	0.19	0.19	0.10	0.11	0.18	0.18	0.22	0.22

$*p < 0.1, **p < 0.05, ***p < 0.01$

market.

Recent research has highlighted that liquidity and liquidity risk has a much larger impact on bond markets than on stock markets. The improvement in data availability for bond transactions has lead to an extensive effort towards understanding the role liquidity plays on bond markets (see, e.g. Bao et al. (2011), Lin et al. (2011), Dick-Nielsen et al. (2012), and Friewald et al. (2012)). In addition, the bond market is an OTC market characterized by search-frictions reenforce the negative effects of asymmetric information (see Duffie et al. (2005) and Duffie et al. (2007)).

We use a comprehensive sample of 3,550 bond issues with a total of 40,012 quarter-bond observations to explore the impact of accounting transparency on bond liquidity. We find a statistically strong and economically large relationship between corporate transparency and bond liquidity. Consistent with the theory of Dang et al. (2012), we find strong evidence of a non-linear relationship. The impact of transparency on bond liquidity is much larger than credit risk and consistent across maturities, issue size, and coupon rate.

We further find that the impact of corporate transparency on bond liquidity is larger during times of distress. This result is consistent when distress is measured as an aggregate shock to market liquidity as has occurred around the collapse of Lehman Brothers or as a liquidity shock to a particular bond when liquidity for a bond issue suddenly dries up. We also find that transparency becomes more important when firms are in financial distress, consistent with the idea that debt markets become more information sensitive when investors are uncertain about a firms' prospects.

Finally, we also document that transparency has a strong impact on liquidity risk, as measured by the (total) variability of a bond's illiquidity measure. This effect is particular strong during the financial crisis. Our results show that only transparent firms experience a higher sensitivity of liquidity risk on accounting transparency during the crisis.

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A Implementation of Liquidity Proxies

In this appendix we describe in detail the implementation of the individual liquidity measures used in the main text. We winsorize the 0.5% highest values of every liquidity variable, meaning that all values above the 99.5% percentile are set to the 99.5% percentile.

Amihud (2002) constructs an illiquidity measure based on the theoretical model of Kyle (1985) and we use a slightly modified version of this measure. It measures the price impact of a trade per unit traded. For each corporate bond, the measure is the daily average of absolute returns r_j divided by the trade size Q_j (in billion \$) of consecutive transactions:

$$\text{Amihud}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|r_j|}{Q_j}, \tag{4}$$

where N_t is the number of returns on day t. At least two transactions are required on a given day to calculate the measure, and we define a quarterly Amihud measure by taking the median of daily measures within the quarter.

Roll (1984) finds that under certain assumptions, the percentage bid–ask spread equals two times the square root of minus the covariance between consecutive price changes:

$$\text{Roll}_t = 2\sqrt{-\text{Cov}(\Delta p_i, \Delta p_{i-1})} \tag{5}$$

where t is the time period for which the measure is calculated. If the covariance is negative, the observation is discarded. The intuition is that the bond price bounces back and forth between the bid and the ask price, and higher percentage bid–ask spreads lead to higher negative covariance between consecutive returns. We define a daily Roll measure on days with at least one transaction using a rolling window of 21 trading days, and the measure is only well-defined if there are at least four transactions in the window. We define a quarterly Roll measure by taking the median of daily measures within the quarter.

Feldhütter (2012) proposes an alternative measure of transaction costs based on what he calls Imputed Roundtrip Trades (IRT). The intuition is the following. Often, we see a corporate bond trading two or three times within a very short period of time after a longer period with no trades. This is likely to occur because a dealer matches a buyer and a seller and collects the bid–ask spread as a fee. When the dealer has found a match, a trade between seller and dealer along with a trade between buyer and dealer are carried out. Possibly, the matching occurs through a second dealer in which case there is also a transaction between the two dealers. If two or three trades in a given bond with the same trade size take place on the same day, and there are no other trades with the same size on that day, we define the transactions as part of an IRT. For an IRT we define the imputed roundtrip cost (IRC) as

$$\mathrm{IRC}_t = \frac{P_{\max} - P_{\min}}{P_{\max}} \tag{6}$$

where $P_{\max}$ is the largest price in the IRT and $P_{\min}$ is the smallest price in the IRT. A daily estimate of roundtrip costs is the average of roundtrip costs on that day for different trade sizes, and we estimate quarterly roundtrip costs by averaging over daily estimates. Feldhütter (2012) examines the properties of IRTs in detail, including how much of total trading volume is captured, and for a subsample of TRACE data with buy–sell indicators available, to what extent IRTs capture full roundtrip costs.

To measure liquidity risk, we take the standard deviation of the daily liquidity measures over a quarter. We require that there be at least six daily observations in a quarter to estimate the standard deviation.

B Implementation of Transparency Proxies

This section describes the details of the proxies for the transparency of the accounting information of a company. For each variable the requires a time series of data, we require a minimum of four consecutive quarterly observation. We use a maximum of eight observations when available.

For our first measure of transparency, we follow the approach by Lang et al. (2012) and use evidence of earnings management as a proxy. Their discretionary earnings smoothing (DES) proxy is based on two earnings smoothness measures commonly used in the literature. The first earnings smoothness measure (S_1) captures the volatility of earnings relative to the volatility of cash flows with the idea being that, the more firms use accruals to manage earnings, the smoother net income will be relative to cash flows (Leuz et al., 2003; Francis et al., 2004). S_1 is measured as the standard deviation of net income before extraordinary items divided by the standard deviation of cash flow from operations, where net income before extraordinary items and cash flow from operations are scaled by average total assets. Cash flow from operations is equal to net income before extraordinary items minus accruals. Accruals (AC) for each company in quarter t are defined as

$$\mathrm{AC}_t = \Delta\mathrm{CA}_t - \Delta\mathrm{CL}_t - \Delta\mathrm{Cash}_t + \Delta\mathrm{STDebt}_t - \mathrm{Depn}_t, \tag{7}$$

where ΔCA is the change in current assets, DCL the change in current liabilities, $\Delta Cash$ the change in cash, $\Delta STDebt$ the change in debt in current liabilities, and $Depn$ the depreciation and amortization expense.

The second earnings smoothness measure (S_2) is the correlation between the cash flow from operations scaled by total assets and total accruals scaled by total assets. The idea behind this measure is that, to the extent that managers create accrual reserves in good times and use them to compensate for poor cash flows in bad times, accruals and cash flows will be more negatively correlated (Lang et al., 2006; Barth et al., 2008). Both smoothing measures (S_1, S_2) are multiplied by negative one so that larger values represent firms with smoother earnings.

The smoothness of earnings relative to cash flows is clearly a natural function of the fundamentals that affect a firms operating environment. In order to determine how transparent earnings are we need to measure the portion in excess of naturally-occurring earnings smoothness. As a consequence, we draw from prior research on the determinants of earnings smoothness and specify an equation designed to capture, to the extent possible, the expected level of earnings smoothness for a firm. We then measure discretionary (excess) smoothing using the residual from the regression specified below:

$$\begin{aligned}S_{i,t} = \alpha &+ \beta_1 \text{LNTA}_t + \beta_2 \text{LEV}_t + \beta_3 \text{BM}_t + \beta_4 \text{STDSALES}_t + \beta_5 \text{PLOSS}_t + \\ &\beta_6 \text{OPCYCLE}_t + \beta_7 \text{SG}_t + \beta_8 \text{OPLEV}_t + \beta_9 \text{AVECFO}_t + \\ &\sum_{a=1}^{18} \alpha_a \text{IND}_a + \sum_{b=1}^{14} \alpha_b \text{QUARTER}_b + \epsilon_t \end{aligned} \tag{8}$$

The right hand side variables are: $LNTA$, the log of total assets measured in millions of U.S. dollars, a measure of firm size; LEV, total debt divided by total assets, to capture differences in financing choices; BM, the ratio of book value to market value of equity, to reflect the extent of the firms intangible assets and expected earnings growth; $STDSALES$, the standard deviation of sales, to capture the volatility of a firms underlying operating environment; $PLOSS$, the proportion of years that a firm experiences losses over the last three to five years, to capture differences in the accruals properties of loss observations; $OPCYLE$, the log of days of accounts receivable plus inventories, to capture the length of the firms operating cycle; SG, the average sales growth to capture growth opportunities; $OPLEV$, net property, plant and equipment divided by total assets, to capture capital intensity; $AVECFO$, average cash flow from operations divided by total assets to capture a firms general level of profitability; and indicator variables for a firms industry IND because the properties of accruals are likely to depend on industry, as well as year indicator variables $YEAR$ to control for macro-economic cycles that could affect earnings cycles.

After we obtain each of the two discretionary smoothness regression residual measures for S_1 and S_2, they are then scaled into percentile ranks, and combined by taking the average. This figure is then subtracted from 1 (so that higher values indicate greater transparency). This variable is referred to as DES and is used to proxy for earnings management in our liquidity regressions. We follow the same procedure for the predicted values obtained from the model for S_1 and S_2 and scale them into ranks and average them. This variable is called fundamental earnings smoothing (FES).

As suggested by Dechow and Dichev (2002) and Francis et al. (2005) accruals quality (AQ) may be an indicator of corporate transparency: Earnings with an accrual component that maps with less variability into the cash flow component may be considered more precise earnings. Specifically, we use the procedure by Francis et al. (2005) and estimate the following cross-sectional regression for each of the Fama and French (1997) 48 industry groups with at least 20 firms in fiscal year t:

$$AC_t = \phi^0 + \phi^1 \text{CFO}_{t-1} + \phi^2 \text{CFO}_t + \phi^3 \text{CFO}_{t+1} + \phi^4 \Delta\text{Rev}_t + \phi^5 \text{PPE}_t + v_t,$$

where AC_t are total current accruals as defined in (7), $CFO_t = NIBE_t - TCA_t$ are cash flow from operations, $NIBE_t$ is net income before extraordinary items, ΔREV_t is the change in revenues, and PPE_t is net value of plant, property, and equipment. The quarterly cross-sectional regression produces firm-quarter residuals. For each firm in each quarter, the residuals are scaled by total assets and then the standard deviation is computed. Given that a higher standard deviation represents lower information quality, we use the negative of this figure as the AQ measure. Finally, we measure earnings precision (EP) as the negative of the standard deviation of earnings, with earnings defined as earnings before extraordinary items deflated by total assets.

C Canonical Correlation Structure

Table C.1: Structure of Canonical Correlations

Panel A reports the weights of the canonical functions from the CCA. Panel B reports the loadings of the canonical functions. These are the correlations of the canonical variates with the variables that make them up. Panel C reports the cross-loadings of the canonical functions. These are the correlations of the canonical variates with the other set of variables.

	Function 1	Function 2	Function 3
Panel A: Canonical Weights			
Standardized canonical coefficients for the independent variables			
DES	-0.003	-0.001	-0.022
EP	0.000	-0.001	0.000
AQ	-0.001	-0.003	-0.001
Analyst	0.000	0.000	0.000
Precision	-0.002	0.002	0.000
Standardized canonical coefficients for the dependent variables			
Amihud	0.000	-0.003	-0.002
Roll	0.001	-0.003	0.009
IRC	0.019	0.013	-0.004
Panel B: Canonical Loadings			
Correlations between the independent variables and their canonical variates			
DES	-0.164	0.079	-0.891
EP	-0.384	-0.550	0.143
AQ	-0.435	-0.741	-0.163
Analyst	-0.488	-0.420	0.254
Precision	-0.895	0.359	0.031
Correlations between the dependent variables and their canonical variates			
Amihud	0.516	-0.818	-0.254
Roll	0.506	-0.545	0.669
IRC	0.998	0.002	-0.059
Panel C: Canonical Cross-Loadings			
Correlations between the independent variables and dependent canonical variates			
DES	-0.047	0.004	-0.022
EP	-0.111	-0.027	0.004
AQ	-0.126	-0.036	-0.004
Analyst	-0.141	-0.020	0.006
Precision	-0.258	0.017	0.001
Correlations between the dependent variables and independent canonical variates			
Amihud	0.149	-0.040	-0.006
Roll	0.146	-0.026	0.017
IRC	0.288	0.000	-0.001

D Disaggregated Results for Liquidity Transparency Panel Regressions

This section reports the results of the regression (2) for each of the three bond illiquidity measures. For ease of comparison, we also report the results for the aggregate *Illiq* measure. Table D.1 reports the results for the aggregate transparency measure (*Trans*) without any controls for credit risk while Table D.2 contains the results with the controls.

Table D.1: Liquidity Transparency Regressions without Controls

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = a_1 \text{Trans}_{i,t-1} + a_2 \text{Trans}^2_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

For each measure of illiquidity, the regression is run (1) only with a linear *Trans* term and (2) with an additional quadratic term. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
Trans	-0.099***	-0.149***	-0.020***	-0.035***	-0.025***	-0.032***	-0.098***	-0.142***
	(-4.71)	(-5.20)	(-3.47)	(-3.73)	(-5.48)	(-5.77)	(-5.29)	(-5.23)
Trans^2		-0.014***		-0.004**		-0.002**		-0.012**
		(-2.62)		(-2.27)		(-2.10)		(-2.46)
Age	0.108***	0.108***	0.009**	0.009**	0.009***	0.009***	0.061***	0.060***
	(8.69)	(8.70)	(2.29)	(2.25)	(6.00)	(5.93)	(6.10)	(6.06)
R^2	0.1682	0.1690	0.1462	0.1474	0.1686	0.1712	0.2265	0.2288

$*p < 0.1, **p < 0.05, ***p < 0.01$

The results for the different illiquidity measures are very similar. For each measure, we find a significant effect of transparency on liquidity (after controlling for bond characteristics). The coefficient in each regression is negative, as expected. We also find that, for each measure, the quadratic term is significant and negative. Hence, the primary results for the aggregate measure also hold for the individual measures of bond illiquidity. Quantitatively, the measured impact is as follows. In the linear specification without controls, a one standard deviation increase in *Trans* decreases illiquidity by 0.131 (*Amihud*), 0.026 (*Roll*), 0.033 (*IRC*), and 0.130 (*Illiq*). This represents a decrease of 19.3, 4.7, 25.6, and 29.9 percent of the respective median values. In the quadratic specification without controls, a one standard deviation increase of *Trans* from its median value decreases illiquidity by 0.234 (*Amihud*), 0.057 (*Roll*), 0.048 (*IRC*), and 0.22 (*Illiq*). This represents a decrease of 34.5, 10.2, 35.5, and 50.7 percent of the respective median values.

We find that our results are robust to the inclusion of these controls. We find that all transparency coefficients remain negative. Also their numeric values are not strongly impacted by the controls. With the controls included in the linear specification with controls, a one standard deviation increase of the *Trans* measure decreases the illiquidity proxies by 0.10 (*Amihud*), 0.020

Table D.2: Liquidity Transparency Regressions with Controls

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = a_1 \text{Trans}_{i,t-1} + a_2 \text{Trans}^2_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

For each measure of liquidity, the regression is run (1) only with a linear *Trans* term and (2) with an additional quadratic term. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
Trans	-0.076***	-0.124***	-0.015***	-0.030***	-0.015***	-0.021***	-0.069***	-0.108***
	(-3.84)	(-4.90)	(-2.76)	(-3.36)	(-5.25)	(-5.20)	(-4.41)	(-4.75)
Trans^2		-0.013**		-0.004**		-0.002*		-0.010**
		(-2.56)		(-2.28)		(-1.73)		(-2.30)
Age	0.108***	0.108***	0.009**	0.009**	0.009***	0.009***	0.062***	0.061***
	(8.92)	(8.92)	(2.45)	(2.40)	(6.54)	(6.48)	(6.43)	(6.38)
IC5	-0.046***	-0.047***	-0.013***	-0.013***	-0.012***	-0.012***	-0.048***	-0.048***
	(-2.85)	(-2.91)	(-2.82)	(-2.86)	(-4.73)	(-4.74)	(-3.73)	(-3.77)
IC10	0.007	0.009	-0.001	-0.001	0.001	0.001	0.003	0.005
	(0.63)	(0.82)	(-0.32)	(-0.17)	(0.92)	(1.11)	(0.46)	(0.68)
IC20	-0.009	-0.009	0.000	0.000	0.001	0.001	-0.001	-0.001
	(-1.18)	(-1.19)	(0.13)	(0.13)	(0.94)	(0.91)	(-0.26)	(-0.26)
IC30	0.002	0.002	-0.000	-0.000	0.000	0.000	0.001	0.001
	(1.00)	(0.96)	(-0.05)	(-0.07)	(0.44)	(0.40)	(0.54)	(0.51)
IS	-0.203*	-0.194*	0.047	0.048	-0.049**	-0.048**	-0.094	-0.091
	(-1.77)	(-1.72)	(1.35)	(1.38)	(-2.24)	(-2.19)	(-0.90)	(-0.87)
DA	0.193	0.169	0.203*	0.201*	0.029	0.026	0.312	0.302
	(0.51)	(0.45)	(1.69)	(1.69)	(0.89)	(0.83)	(1.42)	(1.41)
DC	-0.528	-0.535	-0.231	-0.238	0.061	0.060	-0.207	-0.223
	(-1.24)	(-1.25)	(-1.50)	(-1.54)	(1.36)	(1.34)	(-0.77)	(-0.83)
BM	0.029	0.023	-0.010	-0.011	0.007	0.006	0.038	0.034
	(0.57)	(0.45)	(-0.70)	(-0.78)	(0.67)	(0.59)	(0.80)	(0.72)
Vola	0.590***	0.573***	0.152***	0.148***	0.214***	0.212***	0.752***	0.742***
	(4.13)	(4.17)	(2.63)	(2.60)	(4.44)	(4.43)	(4.84)	(4.92)
R^2	0.1717	0.1726	0.1488	0.1500	0.1894	0.1909	0.2351	0.2368

$*p < 0.1, **p < 0.05, ***p < 0.01$

(*Roll*), 0.020 (*IRC*), and 0.091 (*Illiq*), respectively. Relative to their median values this represents a change of 14.8, 3.5, 14.8, and 21.0 percent, respectively. In the quadratic specification with controls included, a one standard deviation increase of the *Trans* measure from its median value decreases the illiquidity proxies by 0.199 (*Amihud*), 0.050 (*Roll*), 0.033 (*IRC*), and 0.170 (*Illiq*). Relative to their median values this represents a change of 29.3, 9.0, 24.7, and 39.1 percent, respectively. For the controls, we find the expected relationships: Higher *Age* is associated with increased illiquidity. Higher interest coverage (IC) and profit margin (*IS*) is associated with lower illiquidity. The other three credit risk proxies (debt to assets (*DA*), leverage ratio (*DC*), book-to-market value (*BM*)) are not significant for any measure of illiquidity (the correlation coefficient is 0.75). Only the coefficients for *DA* do not have the expected sign as some are negative. This is due to the fact that *DA* is highly correlated with *DC*. Finally, equity volatility is strongly positively related to bond illiquidity.

Tables D.3 and D.4 report the results for the individual transparency measures, without and with credit risk controls.

Table D.3: Liquidity Transparency Regressions without Controls

The table reports the results of the two-way fixed effects panel data regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = \mathbf{a_1} \cdot \text{Transparency}_{i,t-1} + \mathbf{a_2} \cdot \text{Transparency}^2_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

For each measure of illiquidity, the regression is run (1) only with a linear term of the transparency proxies and (2) with additional quadratic terms for each. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
DES	0.022	-0.196	-0.004	0.125	0.007	0.067	0.009	0.197
	(0.26)	(-0.58)	(-0.12)	(1.05)	(0.52)	(1.00)	(0.14)	(0.64)
EP	0.007	-0.123***	0.001	-0.023*	0.002	-0.005	0.007	-0.073**
	(0.55)	(-2.94)	(0.23)	(-1.66)	(0.94)	(-0.91)	(0.66)	(-2.46)
AQ	-0.026	-0.056	-0.011	-0.003	-0.009***	-0.018**	-0.035**	-0.053
	(-1.30)	(-1.32)	(-1.36)	(-0.13)	(-2.99)	(-2.28)	(-2.10)	(-1.35)
Analyst	-0.008***	-0.004	-0.001	0.000	-0.002***	-0.003**	-0.008***	-0.007
	(-2.95)	(-0.53)	(-1.12)	(0.01)	(-4.35)	(-2.13)	(-3.11)	(-0.99)
Precision	-0.097***	-0.059**	-0.015***	-0.014*	-0.023***	-0.030***	-0.095***	-0.095***
	(-5.97)	(-2.47)	(-2.91)	(-1.83)	(-7.85)	(-5.63)	(-9.71)	(-4.88)
DES^2		0.039		-0.140		-0.063		-0.262
		(0.13)		(-1.50)		(-1.13)		(-1.04)
EP^2		-0.014***		-0.003*		-0.001		-0.008***
		(-3.33)		(-1.83)		(-1.36)		(-2.90)
AQ^2		-0.008		0.001		-0.002		-0.005
		(-1.07)		(0.41)		(-1.23)		(-0.64)
Analyst^2		-0.000		-0.000		0.000		-0.000
		(-0.43)		(-0.49)		(0.86)		(-0.00)
Precision^2		0.003		0.000		-0.001*		0.000
		(1.46)		(0.19)		(-1.87)		(0.03)
FES	-0.198*	-0.015	-0.097**	-0.083	-0.047**	-0.035	-0.280***	-0.185
	(-1.88)	(-0.13)	(-2.20)	(-1.56)	(-2.37)	(-1.56)	(-2.63)	(-1.51)
Age	0.107***	0.106***	0.009**	0.009**	0.009***	0.008***	0.060***	0.059***
	(9.21)	(9.16)	(2.36)	(2.34)	(6.32)	(6.16)	(6.42)	(6.35)
R^2	0.1738	0.1755	0.1509	0.1517	0.1912	0.1935	0.2412	0.2425

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table D.4: Liquidity Transparency Regressions with Controls

The table reports the results of the two-way fixed effects panel regression to explain the level of a bond's liquidity:

$$\text{Illiquidity}_{i,t} = \mathbf{a_1} \cdot \text{Transparency}_{i,t-1} + \mathbf{a_2} \cdot \text{Transparency}^2_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

For each measure of illiquidity, the regression is run (1) only with a linear term of the transparency proxies and (2) with additional quadratic terms for each. The variables are described in Section 4 and the data set in Section 5.3. The model is estimated using two-way fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. The last line reports the overall R^2.

	Amihud(1)	Amihud(2)	Roll(1)	Roll(2)	IRC(1)	IRC(2)	Illiq(1)	Illiq(2)
DES	0.021	-0.172	-0.015	0.106	0.003	0.061	-0.012	0.174
	(0.24)	(-0.49)	(-0.50)	(0.88)	(0.26)	(0.94)	(-0.20)	(0.56)
EP	0.008	-0.117***	0.001	-0.025*	0.002	-0.004	0.008	-0.071**
	(0.61)	(-2.91)	(0.14)	(-1.87)	(1.27)	(-0.77)	(0.79)	(-2.53)
AQ	-0.017	-0.035	-0.007	0.006	-0.008***	-0.014**	-0.029*	-0.037
	(-0.80)	(-0.83)	(-0.90)	(0.31)	(-2.76)	(-2.07)	(-1.72)	(-0.98)
Analyst	-0.010***	-0.009	-0.002	-0.001	-0.002***	-0.003*	-0.008***	-0.008
	(-3.81)	(-1.07)	(-1.60)	(-0.42)	(-3.75)	(-1.92)	(-3.17)	(-1.07)
Precision	-0.096***	-0.063**	-0.015***	-0.015**	-0.018***	-0.022***	-0.084***	-0.077***
	(-5.41)	(-2.43)	(-2.85)	(-2.11)	(-7.74)	(-4.53)	(-7.87)	(-3.90)
DES^2		0.021		-0.136		-0.060		-0.258
		(0.07)		(-1.43)		(-1.09)		(-1.03)
EP^2		-0.013***		-0.003**		-0.001		-0.008***
		(-3.28)		(-2.01)		(-1.27)		(-2.92)
AQ^2		-0.006		0.002		-0.001		-0.003
		(-0.74)		(0.65)		(-1.04)		(-0.39)
Analyst^2		-0.000		-0.000		0.000		0.000
		(-0.07)		(-0.20)		(0.72)		(0.02)
Precision^2		0.002		-0.000		-0.000		0.001
		(1.19)		(-0.06)		(-0.82)		(0.43)
FES	-0.209**	-0.027	-0.090**	-0.071	-0.029*	-0.023	-0.237**	-0.149
	(-1.99)	(-0.22)	(-2.04)	(-1.34)	(-1.66)	(-1.09)	(-2.33)	(-1.24)
Age	0.106***	0.106***	0.009**	0.009**	0.009***	0.009***	0.060***	0.060***
	(9.35)	(9.30)	(2.49)	(2.48)	(6.63)	(6.49)	(6.63)	(6.56)
IC5	-0.022	-0.023	-0.010**	-0.010**	-0.007***	-0.007***	-0.030***	-0.029**
	(-1.64)	(-1.63)	(-2.53)	(-2.41)	(-3.18)	(-3.10)	(-2.64)	(-2.55)
IC10	0.001	0.000	-0.002	-0.002	0.000	0.000	-0.002	-0.002
	(0.09)	(0.02)	(-0.56)	(-0.59)	(0.08)	(0.08)	(-0.26)	(-0.30)
IC20	-0.009	-0.010	0.000	0.000	0.001	0.001	-0.002	-0.002
	(-1.27)	(-1.26)	(0.03)	(0.02)	(0.80)	(0.74)	(-0.43)	(-0.44)
IC30	0.002	0.002	-0.000	-0.000	0.000	0.000	0.001	0.001
	(0.98)	(0.87)	(-0.09)	(-0.15)	(0.36)	(0.25)	(0.45)	(0.37)
IS	-0.157	-0.129	0.059*	0.060*	-0.040**	-0.041**	-0.051	-0.042
	(-1.42)	(-1.16)	(1.70)	(1.73)	(-1.97)	(-2.01)	(-0.53)	(-0.43)
DA	0.239	0.196	0.197*	0.204*	0.036	0.041	0.323	0.328
	(0.65)	(0.52)	(1.69)	(1.69)	(1.14)	(1.29)	(1.59)	(1.56)
DC	-0.948**	-0.844**	-0.299*	-0.302*	-0.011	-0.019	-0.548**	-0.528**
	(-2.30)	(-2.02)	(-1.95)	(-1.93)	(-0.29)	(-0.48)	(-2.22)	(-2.12)
BM	0.001	-0.007	-0.017	-0.018	0.002	0.002	0.005	0.002
	(0.02)	(-0.15)	(-1.31)	(-1.31)	(0.24)	(0.21)	(0.13)	(0.05)
Vola	0.281**	0.288**	0.115**	0.112**	0.159***	0.153***	0.524***	0.514***
	(1.96)	(2.14)	(1.98)	(1.97)	(4.20)	(4.02)	(3.93)	(4.00)
R^2	0.1776	0.1787	0.1529	0.1538	0.2004	0.2015	0.2457	0.2466

$*p < 0.1, **p < 0.05, ***p < 0.01$

E Disaggregated Results for Liquidity Risk Transparency Panel Regressions

Table E.1: Liquidity Risk Transparency Regressions with Controls

The table reports the results of the panel data regression model to explain the level of a bond's liquidity:

$$\begin{aligned}\text{Liquidity Risk}_{i,t} &= a_1\text{TRANS}_{i,t-1} + \mathbf{b}\cdot\text{Bond Controls}_{i,t-1}\\ &\quad + \mathbf{c}\cdot\text{Credit Risk Controls}_{i,t-1} + \mathbf{d}\cdot\text{Equity Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}.\end{aligned}$$

The variables are described in Section 4 and the data set in Section 5.3. We follow Petersen (2009) and calculate robust standard errors clustered at the firm level and time dimension. The t-statistics are given in parenthesis. To conserve space, only the coefficients for the transparency variables are reported.

	Amihud Risk	Roll Risk	IRC Risk	Illiq Risk
Panel A: Full Sample				
TRANS	-0.120***	-1.411**	-0.021***	-0.081***
	(-3.87)	(-3.15)	(-4.71)	(-4.50)
R^2	0.08	0.10	0.11	0.13
Panel B: Pre-Crisis Subperiod				
TRANS	-0.073***	-2.294***	-0.027***	-0.098***
	(-3.07)	(-4.06)	(-6.79)	(-8.48)
R^2				
Panel C: Crisis Subperiod				
TRANS	-0.127***	-2.207**	-0.022***	-0.102***
	(-2.75)	(-2.35)	(-3.38)	(-3.80)
R^2				
Panel D: Post-Crisis Subperiod				
TRANS	-0.055***	-0.482	-0.010***	-0.039***
	(-2.87)	(-1.30)	(-4.35)	(-4.18)
R^2				

$*p < 0.1, **p < 0.05, ***p < 0.01$