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Liquidity effects in corporate bond spreads

Jean Helwege^a, Jing-Zhi Huang^b, Yuan Wang^{c,*}^a Department of Finance, the Darla Moore School of Business, University of South Carolina, 1705 College Street Columbia, SC 29208, United States^b Department of Finance, Smeal College of Business, Pennsylvania State University, University Park, PA 16802, United States^c Department of Finance, the John Molson School of Business, Concordia University, 1455 De Maisonneuve Blvd. West, Montreal, QC H3G1M8, Canada

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ABSTRACT

Corporate bond spreads are affected by both credit risk and liquidity and it is difficult to disentangle the two factors empirically. In this paper we separate out the credit risk component by examining bonds that are issued by the same firm and that trade on the same day, allowing us to examine the effects of liquidity in a sample of bond pairs. We examine standard liquidity measures to determine how well they explain the differences in the two bonds' yield spreads and find that the proxies do a poor job of measuring liquidity effects. Incorporating liquidity proxies related to other bonds issued by the firm and those for bonds of other firms can significantly improve the explanatory power. Still, a significant portion of the spread is left unexplained and it is largely driven by a common unknown factor. We conclude that good proxies for the liquidity component of corporate bond spreads remain elusive.

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1. Introduction

A large literature investigates the determinants of corporate yield spreads and links them to credit risk, liquidity and taxes (see, for example, Elton et al., 2001; Delianedis and Geske, 2001; Friewald et al., 2012). Huang and Huang (2012) use structural bond pricing models to show that credit risk accounts for only a small fraction of observed yield spreads if the models are required to be consistent with historical default rates and losses—namely, the credit spread puzzle. Collin-Dufresne et al. (2001) document a large unexplained portion of yield spread changes that is driven mainly by factors that are independent of credit risk. Consequently, many researchers focus on the potential for liquidity to explain a large portion of bond yield spreads (Perraudin and Taylor, 2003; Driessen, 2005; Longstaff et al., 2005; Chen et al., 2007). In addition, Jacoby et al. (2009), Acharya et al. (2010), and Lin et al. (2011) find that liquidity risk is priced in corporate bonds returns.

Disentangling the separate effects of credit risk and liquidity on corporate bond yields, however, is challenging, especially since neither liquidity nor its risk is readily measured. Moreover, studies by Chen et al. (2007), Covitz and Downing (2007), Rossi (2009), and Kalimipalli and Nayak (2012) provide evidence that liquidity effects are comingled with credit risk effects on bond yield spreads.

Consequently, proxies for liquidity may instead capture credit risk. This leads to the following questions: Do bond liquidity proxies really represent the liquidity component of corporate bond yield spreads? If so, how much of the liquidity component can they explain? If they do not have much explanatory power for yield spreads, is it due to the poor performance of the liquidity proxies or to the fact that liquidity risk is small?

We approach these questions by controlling for the credit risk component in corporate bond spreads with a sample of bond pairs. Specifically, we identify pairs of bonds issued by the same firm, that trade on the same day and that have the same bond characteristics.¹ As such, these bonds have the same credit risk and experience the same market variations. Thus, their yields do not differ because of credit risk, taxes or market risk. Instead, the differences in the spreads of the matched bonds (hereafter *DSMB*), if they exist, should reflect the liquidity components of the spreads.

The two bonds in a pair can vary in their trading frequency and volume, offering size, age, and their investors. These differences should explain most of the *DSMB* if liquidity is an important component of bond spreads and it is measured without much error. We use a number of proxies for liquidity to analyze the *DSMB*: three proxies based on prices (the range, the interquartile range (IQR),

* Corresponding author. Tel.: +1 4389360586.
E-mail address: yuanw@jmsb.concordia.ca (Y. Wang).

¹ Other studies that use pairs of matched bonds to control for credit risk include Crabbe and Turner (1995), Helwege and Turner (1999), Huang and Zhang (2008), and Dick-Nielsen et al. (2012).

and Bao et al.'s (2011) illiquidity measure γ), two proxies related to trading activity (trading volume and the number of zero trading days in a month), and three other bond features (age, whether it is an off-the-run bond, and size of the offering). When we regress the *DSMB* on differences in the liquidity proxies we find that liquidity factors are often significant. However, they only explain a small fraction of the difference in the spreads – less than five percent of the cross-sectional variation in the *DSMB*. In a horse race among these eight liquidity proxies, we find that the *Range* measure performs best in that it has the greatest explanatory power and is least affected by credit risk. In contrast, *IQR* and γ lose their explanatory power once credit risk is removed.

One reason for the weak explanatory power of the price-based liquidity proxies is that corporate bonds trade infrequently. Low trading volume and an absence of reliable prices can result in search and delay costs for traders, which is the motivation for the use of these proxies in the analysis of stock market liquidity.² While these measures could work as well when applied to bond prices in actuality the low number of daily trades often makes them less reliable than their counterparts in the equity market. Offsetting this problem, however, is the fact that trades on other bonds provide information about what the price of the untraded bond would be. Thus, we improve on these price-based liquidity measures by incorporating price information from other bonds issued by the same firm to create firm level measures of liquidity. Likewise, we aggregate price information on bonds issued by other firms as well to create market level measures of *Range*, *IQR*, and γ . Market level measures should provide traders with a sense of how liquidity risk varies with market conditions when the firm's bond prices are unavailable. We find that these measures of liquidity have significant explanatory power in *DSMB* regressions, indicating that liquidity risk varies with firm and market conditions.

Our findings suggest that liquidity has a significant effect on corporate bond yields, supporting past research that uses these proxies to control for liquidity in bond spread regressions. However, our results also indicate that proxies for liquidity often capture credit risk as well as liquidity. Moreover, it appears that both effects vary over time, making it even more difficult to empirically separate the two components of corporate bond yields.

Our work is closely related to that of Crabbe and Turner (1995), who investigate pairs of newly issued bonds that differ only in their face value and find no impact of liquidity differences. Another related study is by Dick-Nielsen et al. (2012), who use matched pairs as part of their analysis of liquidity premia during the recent financial crisis.

The remainder of this paper is organized as follows. Section 1 presents the research design, describes the liquidity proxies, and provides details of the data used in our analysis. Section 2 contains empirical results while Section 3 concludes the paper.

2. Liquidity proxies and tests of liquidity effects

A large literature on equity liquidity investigates measures of liquidity related to stock prices, trading volume and transaction costs (e.g., studies by Amihud and Mendelson (1986, 2006), Lee and Ready (1991), Huang and Stoll (1996), Lesmond et al. (1999; LOT), Amihud (2002), Acharya and Pedersen (2005), Lesmond (2005), and Hasbrouck (2009)). As far as possible these measures are also used to proxy for liquidity in the corporate bond market, but sparse trading and limited data often prohibit their use in this market (Edwards et al., 2007; Goldstein et al., 2007). Frequently, researchers use other proxies for liquidity that reflect the institutional features of the corporate bond market. Below we discuss

these proxies in the bond literature and how they are used to test the impact of liquidity on bond spreads.

2.1. Liquidity proxies

A number of problems with studying liquidity in corporate bonds arise from the fact that corporate bonds trade only infrequently (Edwards et al., 2007; Goldstein et al., 2007). Bonds are especially unlikely to trade if they have found their way into the portfolios of buy and hold investors such as insurance companies and pension funds (Sarig and Warga (1989)). Thus, researchers frequently proxy for the liquidity of a corporate bond with its age (Alexander et al., 2000; Goldstein et al., 2007; Hotchkiss and Jostova, 2007; Mahanti et al., 2008; Ronen and Zhou, 2010; Goldstein and Hotchkiss, 2012). Bond liquidity is also often measured by the face value of the bond issue (*Size*).³ The logic behind *Size* is that the larger the offering amount, the larger the number of investors who own the bond and therefore the lower the search costs. Another measure to indicate trading activity is the *Percentage of zero trading days* or the *LOT* measure (Chen et al., 2007).

Unlike data on stock transactions, the bid-ask spread is rarely used for corporate bonds because the common databases (TRACE and the Lehman Fixed Income Database) do not include bid and ask prices (Schultz, 2001) and those that do, such as the Mergent data based on insurance company trades and TRACE after 2008, include so few sales of bonds that the bid and ask prices are not often available on the same day.

In this study, we consider the following eight liquidity measures: *Percentage of zero trading days*, *Bond size*, *Bond age*, *Cumulative trading volume*, *On/off-the-run indicator*, *Range*, γ , and *Inter-quartile Range (IQR)*. The *Percentage of zero trading days* is defined as the number of zero return days in the previous month. The *on/off-the-run indicator* is defined to be one if the bond age is less than 2 months and zero otherwise. We set this cut-off by relying on the finding in Ambrose et al. (2007) that bond trading drops dramatically 2 months after issuance.

Range and *IQR* are two liquidity measures used by Han and Zhou (2008). Similar to Amihud's (2002) price impact measure as well as the volatility impact measure used by Downing et al. (2005), *Range* is defined as follows:

$$Range_t^i = \frac{\max_j (p_{j,t}^i) - \min_j (p_{j,t}^i)}{Q_t^i} \times 100 \quad (1)$$

where $p_{j,t}^i$ is the price from trade j on day t for bond i ; \bar{p}_t^i is the average price of bond i on day t ; and Q_t^i is the total trading volume of bond i on day t . The measure gives the volatility in price caused by a given volume of trades. The logic behind this is that less liquid bonds tend to have higher price volatility for a given level of trading volume.

The inter-quartile range (*IQR*) is defined as the difference between the 75th percentile and 25th percentile of prices for one day normalized by the average price on that day. That is,

$$IQR_t^i = \frac{p_t^{i,75th} - p_t^{i,25th}}{\bar{p}_t^i} \times 100 \quad (2)$$

This measure should be affected more by the bid-ask spread than *Range* since price volatility is mostly a result of the bid-ask bounce when there is no information about fundamentals. Information about credit risk should lead to larger price movements, and this variation is more likely to be eliminated by using the 75th and 25th percentiles. Hence, the data should be less sensitive to outliers than *Range*.

³ See for example, Crabbe and Turner (1995), Hong and Warga (2000), Houweling et al. (2005), and Hotchkiss and Jostova (2007).

² See Amihud and Mendelson (2006) and Schwarz (2010).

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