**Firm Visibility and Corporate Bond Liquidity**

Oliver Chang

Simi Kedia

Jason Wei

Xing Zhou[[1]](#footnote-1)

**Abstract**

This paper examines the impact of firm visibility on bond liquidity. Using a range of visibility measures such as firm size, advertising expenses, breadth of stock and bond ownerships, and analyst coverage, we find strong evidence that visibility positively impacts bond liquidity. Our result is robust to alternative measures of liquidity and different estimation methodologies, and holds for bonds in all rating categories. To further prove the direct link between firm visibility and bond liquidity, we examine liquidity changes in bonds upon their issuing firms being added to the S&P 500 index, an exogenous visibility increasing event. We find a significant increase in bond liquidity relative to a control group after the index inclusion.

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It has been shown in the literature that firm visibility affects stock liquidity and investors’ stock selection. It is also known that, in the fixed income market, liquidity affects the yield spreads of corporate bonds. Insofar as liquidity is an important pricing factor for bonds and firm visibility influences stock liquidity, it is natural to ask whether firm visibility also affects bond liquidity. In this paper, we establish a strong link between bond liquidity and firm visibility, in addition to the commonly known liquidity determinants.

The importance of bond liquidity has been well recognized both in the industry and in academia, partly due to the fact that corporate bonds have much lower liquidity compared with equity. In a recent survey conducted by the International Capital Market Association (ICMA), liquidity was ranked as the most important factor in bond trading. The lack of transparency and liquidity in the corporate bond markets was stressed by Arthur Levitt, the former Chairman of the SEC, in a 1998 speech that prompted the establishment of Trade Reporting and Compliance Engine (TRACE).[[2]](#footnote-2) In the academic world, several papers (e.g., Chen, Lesmond and Wei (2007)) have documented that bond liquidity is priced and affects yield spreads. Although researchers have linked basic bond characteristics to liquidity, it is generally not known what drives the cross-sectional differences in bond liquidity. Why do bonds with similar characteristics such as age, maturity, offering size and credit risk have different levels of liquidity? While the answer to this question may potentially hinge upon many factors, in this paper, we focus on the role of firm visibility.

Firm visibility has been known to impact stock selection and liquidity. Several prominent equity fund managers (e.g., Peter Lynch and Warrant Buffet) have espoused the philosophy of “buying what you know.” Individual retail investors also appear to make their investment decisions based on familiarity as documented by Huberman (2001), and Grinblatt and Keloharju (2001). Firm visibility has also been shown to impact stock liquidity through various channels. For instance, Grullon, Kanatas and Weston (2004) document that the enhanced visibility from advertising has a positive impact on stock liquidity; Kadlec and McConnell (1994), and Foester and Karolyi (2001) show that newly listed stocks on the NYSE enjoy a decrease in bid-ask spreads in response to the increased visibility. While the impact of visibility on stock liquidity has been well documented, little is known about how firm visibility might impact liquidity in the bond market.

We fill this gap by examining whether bonds issued by highly visible firms are likely to enjoy higher liquidity. We employ several proxies to capture firm visibility. Our first proxy is firm size. Larger firms are more likely to be visible and known to capital market participants. The second proxy is the firm’s advertising expense as in Grullon, Kanatas and Weston (2004). The next two proxies capture visibility in the equity markets. The first of these, the number of institutions holding the firm’s stock, captures the breadth of institutional ownership and represents visibility in the equity markets.[[3]](#footnote-3) The other proxy, the number of analysts following the firm, also measures the visibility in the equity market. The larger the number of analysts, the greater visibility they create for the firm.

We also use multiple proxies for bond liquidity. The first measure of liquidity, based on Chen, Lesmond and Wei (2007), is the percentage of days in the quarter the bond has zero returns. We also use the number of trades in the quarter and the total par value traded as measures of liquidity. Our last set of proxies, the gamma (γ) of Bao, Pan and Wang (2011) and the Amihud’s illiquidity measure (Amihud, 2002), are based on transaction prices and volume and are described in detail in the data section. We find a significant positive impact of visibility on bond liquidity. In the univariate analysis, a move from the lowest visibility quartile to the highest is associated with a reduction in percentage of zero returns ranging from 23% to 33%, depending on which visibility proxy is in use. Similarly, the number of trades in the highest visibility quartile is three to six times larger than that in the lowest visibility quartile. The gamma (γ) of the highest visibility quartile is also substantially lower than the lowest visibility quartile.

The positive relation between bond liquidity and firm visibility continues to hold in multivariable analyses that control for bond and firm characteristics that are known to impact liquidity. The multivariate results are robust across all proxies of visibility and liquidity and across alternative estimation methods such as Fama-McBeth regressions and pooled regressions. The impact of visibility on liquidity exists in subsamples of both high-yield bonds and investment grade bonds. Not only significant statistically, the impact of visibility on liquidity is also significant economically. For instance, when liquidity is measured by the percentage of zero returns, a move from the first to the third quartile of visibility is associated with a 15.6% to 18.4% increase in liquidity from its mean, depending on which visibility proxy we use.[[4]](#footnote-4)

As an additional analysis, we also relate liquidity directly to visibility of the bond market. To this end, we use as a proxy the average number of institutions in the past four quarters that hold bonds issued by the same firm. We find a significant positive effect of bond visibility on liquidity, over and above the impact of other measures of firm visibility. A move from the first to the third quartile of bond visibility is associated with an 11.4% increase in liquidity from its mean.

Notwithstanding controlling for various firm/bond characteristics and the careful design of visibility and liquidity proxies, the observed relationship between liquidity and visibility might simply be a manifestation of our visibility measures capturing other missing characteristics that influence bond liquidity. To address this concern, we examine changes in bond liquidity around an exogenous event involving an increase in visibility, viz. the addition of stocks to the S&P 500 index. The addition to the S&P 500 index increases a firm’s visibility while not altering any other characteristics of the firm or bond that are likely to influence bond liquidity. We find a significant increase in bond liquidity in the quarter following the addition to the S&P 500 index relative to the preceding quarter and to a control sample.

The paper proceeds as follows. Section 1 discusses the related literature. Section 2 describes the data and our measures of visibility and liquidity. Section 3 presents our main empirical results. Section 4 discusses the impact of S&P 500 index additions and Section 5 concludes.

**1. Literature review**

Our paper is related to several strands of literature. As discussed earlier, the paper is closely tied to the literature documenting the role of visibility and familiarity in stock selection and liquidity. In particular, Huberman (2001), and Grinblatt and Keloharju (2001) show that individual investors are more likely to buy familiar stocks. Grullon, Kanatas and Weston (2004) document that, in addition to stock holdings, visibility, as captured by advertising expenses, also impacts stock liquidity. Furthermore, as shown by Kadlec and McConnel (1994), and Foester and Karoli (2001), when a firm is being listed on the NYSE for the first time which constitutes a visibility increasing event, the liquidity of its stock (measured by bid-ask spreads) improves significantly.[[5]](#footnote-5) Despite numerous studies examining the impact of visibility on stock selection, liquidity and returns, the literature has been silent on the potential role of visibility in the liquidity of corporate bonds. Our paper fills this gap.

Our work is also related to the recent and emerging literature that examines the determinants of bond liquidity. For instance, Hotchkiss and Jostova (2007) examine bonds in the dataset of National Association of Insurance Commissioners (NAIC) over the period of 1995 to 1999 and document the role of firm and bond characteristics in shaping up bond liquidity. They find that trading volume increases in issue size but decreases in bond age. They also report that, as far as their impact on liquidity is concerned, credit risk plays a bigger role in high-yield bonds while interest-rate risk exerts a bigger influence in investment-grade bonds. When examining the impact of visibility on bond liquidity, we control for a battery of firm/bond characteristics known to affect liquidity. We also examine investment-grade and high-yield bonds separately for robustness.

Ultimately, our study is related to the literature documenting that liquidity is an important factor affecting bond yields and returns. Motivated by the finding that credit risk determinants cannot fully explain yield spreads of corporate bonds (Collin-Dufresne, Goldstein and Martin (2001), and Huang and Huang (2003)), and that liquidity might be a potential determinant (Longstaff, Mithal and Neis (2005)), Chen, Lesmond and Wei (2007) undergo thorough empirical investigations and show that liquidity is priced in both the level and changes in yield spreads. Their finding is subsequently confirmed by many other studies (e.g., Bao, Pan and Wang (2011), Friewald, Jankowitsch, and Subrahmanyam (2010)). Meanwhile, Lin, Wang and Wu (2011) and Acharya, Amihud and Bharath (2012) demonstrate that liquidity risk is also priced in corporate bond returns. All these studies underscore the importance of understanding the determinants of bond liquidity, an issue the current paper attempts to shed light on.

**2. Data description**

We start with a sample of corporate bonds whose transaction information was disseminated through FINRA’s TRACE system during the period 2003-2010. Upon its initiation on July 1, 2002, TRACE only disseminated transaction information on large investment-grade and 50 high-yield issues. Subsequently, TRACE experienced three stages of implementation when the dissemination was expanded to include smaller and less liquidity issues. On February 7, 2005, TRACE began to cover almost all over-the-counter bond transactions but Rule 144A corporate bonds. Several filters are applied to the bond transaction data from TRACE before we estimate liquidity measures. We eliminate the following bonds/transactions: when-issued, cancelled, subsequently corrected, reversed trades, and commission trades. In addition, trades with special prices, special sales conditions, and longer than 2-day settlements are also removed. We also delete potentially erroneous records such as transactions with missing price or quantity values, par-value not a multiple of $1,000, price outside the range of 10 and 200, yield is either zero, negative or above 100%, and price reversals over 20 percent in adjacent trades. After we retrieve bond characteristic information, including credit rating histories from Mergent’s FISD database, and merge it with TRACE data, we end up with a sample of 30,718 bonds issued by 4,080 firms.

For 6,613 bonds by 1,636 issuers, we are able to obtain stock trading data from CRSP and firm accounting information from COMPUSTAT. Further, as two of our visibility measures are based on mutual fund holding and analyst coverage, we require the issuer to have available data on Thomson 13f Filings and I/B/E/S. This gives us a sample of 5,635 bonds by 1,360 firms. It should be noted that, requiring the presence in the Thomson 13f Filings and I/B/E/S datasets entails a sample of large firms which already enjoy high visibility and better liquidity for their bonds. As such, the documented importance of firm visibility in this sample will likely underestimate the true impact of firm visibility on bond liquidity.

As shown in Panel A of Table 1, the bonds in our sample are generally large issues with a mean issue size of $480.95 million. Bonds with trading information are relatively young, with an average age of slightly over two years, and tend to be long term bonds, with an average time to maturity of over 10 years. About 63% of the bonds are investment grade, and over 22% are from the finance industry (see Panel B). Most of the bonds analyzed in this paper carry some embedded options: About 68% (10%) are callable (puttable) and over 15% are convertible. Finally, very few bonds have sinking fund provisions (0.64%) and variable coupon rates (1.4%), but most of them carry some covenants (over 91%).

*2.1 Measures of visibility*

We use several measures of firm visibility. The first measure or proxy is firm size (SIZE) since larger firms are more likely to be visible. We measure firm size in the prior fiscal year as the market value of equity plus the book value of debt. The average firm size is about $14 billion (see Panel A of Table 2).

The second measure of firm visibility is the advertising expenditure in the prior fiscal year (XAD). Grullon, Kanatas and Weston (2004) document that advertising increases the visibility of the firm not only in the product market but also in the equity market. Logically, the increase in visibility due to advertising should also extend to the bond market and hence improve bond liquidity. As shown in Panel A of Table 2, the average advertising expenditure is $202,250, much higher than the median of $29,660. Note that this measure is available for only 555 of the total 1,360 firms in the sample.[[6]](#footnote-6)

Our third proxy, the average number of institutions holding the firm’s stock in the previous four quarters (NEQUITY), captures a firm’s visibility in the equity market. This measure of breadth of institutional ownership has been used in the prior literature to capture investor recognition and visibility in the equity market (see, e.g., Kadlec and McConnell (1994); Grullon, Kanatas and Weston (2004); Lehavy and Sloan (2008); and Bodnaruk and Ostberg (2009)). Averaging the numbers of institutions over the prior four quarters helps avoid the potential influence of temporary changes in ownership.

The fourth measure, the average number of analysts following the firm in the prior four quarters (NANALYST), is also based on equity market visibility. The rationale of averaging over the previous four quarters is the same as that for the NEQUITY measure. One of the advantages of using equity market visibility is the fact that it captures visibility specific to the capital market as opposed to the firm alone.

Panel A of Table 2 displays the summary statistics for the number of institutions and the number of analysts at the firm level. The average number of institutions that hold the firm’s stock is 256, compared with a median of 183. The average (median) number of analysts following the firm is 10 (9). These numbers are higher than the averages for the universe of firms on Compustat as our sample biases towards larger and more established firms. Even though the average visibility is high in our sample, there are significant cross-sectional variations to allow us to examine the impact of visibility on bond liquidity.

As expected, the different measures of visibility are correlated with each other, as shown in Panel B of Table 2. The highest correlation of 0.65 is between firm size (SIZE) and the institutional ownership (NEQUITY). The lowest correlation of 0.259 is between advertising expenses (XAD) and the number of analysts (NANALYST). The less-than-perfect and lower correlations suggest that the measures likely capture differing aspects of visibility, justifying the use of all of them in the analysis.

*2.2 Measures of liquidity*

Our first measure of liquidity is the fraction of days in a quarter on which the bond has a return of zero (ZEROPCT). This measure has been used in several previous papers starting from Chen, Lesmond and Wei (2007). For our purpose, we also treat all days with no trading as days with a zero return. The lower the number of zero-return days in a quarter, the higher the liquidity. As seen in Panel C of Table 2, the mean ZEROPCT for bond/quarters in our dataset is 0.68, indicating that most of the bonds are traded infrequently, if at all. Consistent with the notion that liquid bonds tend to trade more often, we also use the total number of trades (NTRADES) and total par value of transactions (VOLUME) within a quarter to measure liquidity.[[7]](#footnote-7) The average number of trades in a bond within each quarter is 214. The distribution of the number of trades is skewed as the median is only 61 trades. This is consistent with the fact that most corporate bonds are traded at low frequency while a small fraction of them are traded fairly frequently (see, e.g., Ronen and Xing (2010)). The average trading volume in a bond within each quarter is $75.9 million.

In addition, we also estimate the γ measure (GAMMA) proposed by Bao, Pan and Wang (2011). We calculate the volume-weighted daily price for each bond and then estimate GAMMA for each bond/quarter by computing the magnitude of negative auto-covariance in daily price changes within each quarter. This measure is aimed at capturing the transitory price movements in bond prices. Our last measure is the Amihud illiquidity measure (AMIHUD). To estimate the Amihud measure at the bond/quarter level, we first calculate the price impact for each bond/day by dividing the absolute changes in volume-weighted daily prices by daily trade volume, whenever prices for two consecutive trading days are available. We then average the daily price impact across days within each quarter for each bond to obtain a bond/quarter level estimate.

Panel D of Table 2 displays the correlations between the different measures of liquidity. All correlation coefficients are statistically significant at the 1% level and have the expected sign. The correlation between GAMMA and AMIHUD is 0.322, lower than the correlations between trade-based measures (viz. ZEROPCT, NTRADES and VOLUME). Their correlations with the trade-based measures are even lower. This is consistent with the fact that liquidity is a multi-dimension concept and different measures tend to capture its different aspects.

**3. Empirical results**

*3.1. Univariate tests*

We begin by examining univariate evidence on the difference in liquidity between bonds issued by more visible and less visible firms. All bond/quarters are sorted into quartiles according to firm visibility and Table 3 reports the mean and median of each quartile under each of the liquidity measures. As seen in Panel A, ZEROPCT decreases monotonically as visibility increases, regardless of which proxy we use for visibility. Moreover, the difference in mean or median between the first and the fourth quartiles is significant at the 1% level for all measures of visibility.

Panels B and C report similar results for the other two trade-based liquidity measures: NTRADES and VOLUME. Not only increasing monotonically as visibility increases, bond liquidities are different between the two extreme quartiles at the 1% level. The differences are also economically significant. For instance, the average number of trades of the most visible quartile is 3 to 5.7 times that of the least visible quartile. The corresponding multiples for the average trading volume are around 3.

Finally, Panels C and D present results for the last two liquidity measures: GAMMA and AMIHUD. Once again, bond liquidity increases with firm visibility. Monotonicity prevails in all cases but one: the AMIHUD measure of liquidity when visibility is measured by the advertising expenditure (XAD). Otherwise, the differences in liquidity between extreme quartiles are also significant at the 1% level. Notice that we do not observe multiples (contrasting the extreme quartiles) comparable to the trade-based liquidity measures. This is due to the fact that the last two liquidity measures are much less skewed.

*3.2. Multivarite analysis*

Although the univariate analysis points to the significant impact of visibility on bond liquidity, it does not control for other liquidity determinants. To properly assess the impact of visibility amongst all liquidity determinants, we need a multivariate framework. This is the focus of the current section. We estimate the following Fama-MacBeth (1973) regression:

 (1)

The main explanatory variable is Visibility, measured by firm size (SIZE), advertising expenditure (XAD), the number of institutional owners of the firm’s stock (NEQUITY), and the number of analysts following the firm (NANALYST).

Following the literature,[[8]](#footnote-8) we include several control variables. First, we include a bond’s age since issuance (AGE) and the logarithm of its total amount outstanding (DAMOUNT), since Hotchkiss and Jostova (2007) document that issue size and age are the two most important determinants of liquidity. Time to maturity (TTM) is also included. In addition, we include three dummy variables to reflect a bond’s credit rating. The dummy variable BBBDum takes the value of one if the credit rating is at BBB or higher; the dummy variable BaboveDum takes the value of one if the credit rating is BB or B; and finally the dummy variable CCCbelowDum takes the value of one if the credit rating is at CCC or lower. Otherwise all the dummy variables take the value of zero.[[9]](#footnote-9) We control for the issuer’s industry classification by including two dummy variables for the Finance and Utility industries (FinanceDum and UtilityDum). We also include a battery of dummy variables on bond complexity features: embedded call or put option (OptionDum), convertibility (ConvertibleDum), sinking fund provisions (SinkfundDum), variable coupon rates (VarcouponDum), whether the issue is offered to global investors (GlobalDum) and whether the bond has any covenant (CovenantsDum). Lastly, as liquidity in a bond is also affected by firm specific news, we include trade volume (Stkturnover) and absolute abnormal returns (Absstkret) of the issuer’s equity. The Newey-West procedure is used to adjust the standard errors. To conserve space, we report the complete results for the ZEROPCT liquidity measure in Table 4 and the partial results for all the other liquidity measures in Table 5 as robustness checks.

As seen in Table 4, when liquidity is measured by ZEROPCT, visibility exhibits significant impact on the liquidity of the issuer’s bonds even after controlling for other liquidity determinants. The coefficients for all visibility measures are negative and significant at the 1% level, confirming the positive relationship between visibility and liquidity. Further, the effect of firm visibility is also economically significant. An increase in firm size from the first to the third quartile is associated with an 18.4% decrease in ZEROPCT from its mean (see Column 1).[[10]](#footnote-10) Similar effects are observed when using XAD (NEQUITY) to measure firm visibility. A move from the first to the third quartile of XAD (NEQUITY) is associated with a 16.3% (15.6%) decrease in ZEROPCT from its mean. The economic significance is lower when we use NANALYST as the visibility measure. An increase in analyst coverage (NANALYST) from the first to the third quartile is associated with a 6% decrease in ZEROPCT.

The estimates of the coefficients of other control variables are generally consistent with previous studies. For example, the coefficient for age is positive while that for the total amount outstanding is negative, consistent with the fact that seasoned and small bond issues tend to be less liquid. We find that long-term bonds tend to be less liquid. However, liquidity is not necessarily lower for lower-rated bonds. In addition, liquidity is higher for convertible bonds and bonds offered to global investors, but lower for bonds with variable coupon rates. Furthermore, bond liquidity is positively related to the issuer’s equity liquidity and returns. Finally, whether a bond has sinking fund provisions and covenants does not seem to have strong impact on liquidity, nor does a bond’s industry classification.

*3.3 Robustness checks*

In this section, we conduct a number of robustness checks. First, we re-estimate model (1) using other measures of liquidity and the results are presented in Table 5. Estimates on the control variables are omitted for brevity. We continue to find significant evidence that bonds issued by visible firms tend to be more liquid. Regardless of which visibility measure is used, the visibility coefficient is positive and significant at the 1% level when NTRADES or VOLUME is used to measure bond liquidity (see Panels A and B). When GAMMA and AMIHUD are used to measure liquidity, the visibility coefficient is negative and significant. The only exception is with the XAD/AMIHUD combination as shown in Panel D.[[11]](#footnote-11) Overall, our results are robust to the use of different measures of liquidity and visibility.

Second, to control for the potential influence of time varying factors on bond liquidity, we re-estimate model (1) using a pooled regression. In addition to the control variables on bond and firm characteristics, we also include variables on general market and macroeconomic conditions. Shocks to the equity market, estimated by the absolute value of the return on the S&P 500 index (AbsSP500ret), is used to measure the general market condition. This variable captures the potential investment flows and the dynamics of liquidity across the stock and bond markets. Moody’s corporate credit spreads between Baa and Aaa bonds (BAA\_AAA) is used to measure the general bond market liquidity since the demand for higher quality bonds increases relative to the lower quality bonds during illiquid periods. In addition, we include the absolute value of the return on 10-year Treasury bonds (AbsT10Yret) to capture the potential impact of shocks to long-term interest rates on the trading of corporate bonds. Since our sample includes multiple bonds by the same issuer over multiple periods, we correct the standard errors following Thomson (2009) to account for potential correlations across bonds and over time. Table 6 shows that the coefficients for all visibility measures remain negative and highly significant. In sum, our results are robust to this alternative specification.

Lastly, based on the finding that liquidity determinants affect high-yield and investment-grade bonds differently (Hotchkiss and Jostova (2007)), we examine whether the effect of visibility differs across credit rating groups by re-estimating model (1) separately for bonds in these two rating categories. As shown in Table 7, visibility is important for both subsamples of bonds. Panel A shows that the coefficients for visibility measures are all negative and significant at the 1% level for investment-grade bonds. Similar effect is documented for high-yield bonds in Panel B. All measures of visibility, with the exception of XAD, are negative and significant at the 1% level. the coefficient of XAD is significant at the 10% level.

*3.4. Visibility in the bond markets*

In this section, we develop a direct measure of bond market visibility and then explore its impact on bond liquidity. It is quite likely that over and above the firm and equity-market visibility, the specific bond-market visibility is also important for bond liquidity. Consistent with the measure of visibility in the equity market, i.e., the number of institutions that hold the firm’s equity, we use the number of institutions holding the firm’s bonds as a measure of bond visibility.

We obtain bond holdings by institutions from the Lipper eMAXX database for the period of 2003 to 2008. This database includes bond holdings by almost all insurance companies, over 95% of the existing mutual funds and the top 250 public pension funds. The rest are held by hedge funds, other pension funds, banks, private investors, and foreign entities for which Lipper is not able to track holdings. This data on quarterly bond holdings has been analyzed by Dass and Massa (2011) and Massa, Yasuda and Zhang (2010). We first check the representativeness of the dataset by examining the share of the outstanding bonds that are held by all institutions reported to Lipper. For each bond/quarter, we aggregate the amount of holdings by all institutions and divide it by the total amount outstanding.[[12]](#footnote-12) We compare it to the summary statistics on bond holdings obtained from a large custodian bank (State Street Corporation or SSC) and reported in a recent study by Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008). We find that Lipper has a broader coverage than SSC except for bonds that mature in less than one year. Lipper’s coverage is about 38.92 % of the total amount outstanding relative to SSC’s 14.53%.

For each bond/quarter over the period of 2004 to 2008, we calculate the average number of institutions that hold the bond over the previous four quarters (NBONDS). After merging the holdings with our previous sample, we have a total of 4,814 bonds issued by 1,277 firms. The mean and median of NBONDS is 57 and 32, respectively. This bond visibility measure also exhibits varying degrees of correlation with firm and equity visibility measures. Its correlation with SIZE and NEQUITY is around 0.76, whereas its correlation with XAD and NANALYST is 0.48 and 0.47, respectively. The less-than-perfect correlations with the other visibility measures suggest that the bond-market visibility measure can capture other aspects of visibility.

To estimate the impact of bond visibility, we re-estimate model (1) using NBONDS as the visibility measure. As shown in Column I of Table 8, the coefficient of NBONDS is negative and highly significant. The more institutions that hold the bond in the prior year, the lower the ZEROPCT measure.[[13]](#footnote-13) This result is robust to including proxies for firm and equity visibility (See Columns II to V). Further, the impact of bond visibility on liquidity is also economically significant. Based on the results in Column II, moving from the first quartile to the third quartile of NBONDS is associated with a decrease in ZEROPCT of around 11.24% from its mean. Note that this effect is after controlling for firm visibility as captured by firm size.[[14]](#footnote-14)

**4. Additions to the S&P 500 index**

So far we have shown that firms with higher visibility enjoy greater bond liquidity. A legitimate concern is that some omitted firm characteristics may be driving these results. In other words, some unobservable firm characteristic may be associated with our visibility measures as well as bond liquidity. We address this concern by studying an exogenous event that unambiguously increases a firm’s visibility: its inclusion in the S&P 500 index. Since being chosen as a component stock of the S&P 500 index is a mere confirmation of the firm’s overall profile, the event itself does not generate new information on any aspect of the firm’s fundamentals. In fact, Standard and Poor’s explicitly claims that additions and deletions do not reflect their opinion on or investment merits of the firm. However, addition to the index does raise the firm’s visibility. Hence the increase in liquidity, if occurring right after the addition, can be unambiguously attributed to increased visibility.

Over our sample period of 2003 to 2010, 49 firms with 119 bonds outstanding were added to the S&P 500 index. For each bond, we identify the quarter prior to (Pre\_Addition) and the quarter after (Post\_Addition) the announcement of the S&P 500 index adjustment and then calculate the average liquidity for each period. As can be seen in Panel A of Table 9, for the full sample, there is a significant decrease in ZEROPCT from the pre-announcement period to the post-announcement period. This difference is significant at the 1% level for both the mean and the median. Similar results are obtained for the number of trades (NTRADES) and trading volume (VOLUME), both of which more than double from the quarter prior to the announcement to the quarter after the announcement.[[15]](#footnote-15)

Our claim that the additions to the S&P 500 index are exogenous, non-informational events is actually consistent with the existing literature. For instance, Shliefer (1986) examines and rules out the possibility that the associated stock price increase around S&P 500 index addition is caused by “good news.” In particular, Shleifer (1986) postulates that if the additions convey good news, the stock price reaction should be higher for firms with lower-rated bonds. However, he fails to obtain evidence supporting this conjecture. He thus concludes that the increase in stock returns is actually driven by a downward sloping demand curve as opposed to good news. However, in a recent paper, Denis, McConnell, Ovtchinnikov and Yu (2003) find that, although the addition to the S&P 500 index is not information driven, the firm inclusion into the index improves a firm’s prospects as evidenced in improved earnings in the current and the next fiscal year. To rule out the possibility that this expectation of improved future performance might potentially cause an increase in bond liquidity, we examine the impact on bond liquidity separately for investment grade and high-yield bonds. If the good-news or good-prospect effect exists, then we should see a bigger impact on liquidity for high-yield bonds. Of the 119 bonds in the sample there are 47 high-yield bonds and 72 investment grade bonds.

As seen in Panel A of Table 9, under all measures, bond liquidity increases after the firm is added to the S&P 500 index, regardless of which rating category the bond belongs to. If anything, the liquidity improvement is more pronounced with the investment grade bonds, directly contradicting the good-news or good-prospect hypothesis. Hence it is quite reasonable to attribute the liquidity improvement to increased visibility. In fact, precisely because of the higher visibility of the newly added firms to the S&P 500 index, more insurance companies and pension funds, which tend to invest in investment grade bonds to lower risk capital or to comply with regulations, start to hold and trade more such bonds from these firms.

Although we have ruled out the changes in a firm’s fundamentals (in the form of either good news or good prospects) around the index addition, it is still possible that every announcement is accompanied with or prompted by changes in certain market-wide factors, which in turn could cause common movements in liquidity. To address this concern, we perform a difference-in-difference test using a control sample. Specifically, for each bond in our sample of S&P 500 index additions, we identify all other bonds having a similar credit rating and time to maturity and calculate their average liquidity. This average is then subtracted from the liquidity of our sample bond to obtain a control-adjusted liquidity measure. We do this for the full sample as well as the subsamples of investment and high-yield bonds. As seen in Panel B of Table 9, there is a significant increase in control-adjusted liquidity after the index addition announcement, suggesting that the observed liquidity increase is due to increased visibility instead of market-wide factors. Incidentally, the difference in difference is also more pronounced with investment grade bonds.

**5. Conclusions**

This paper examines the impact of firm visibility on corporate bond liquidity. We capture the visibility of a firm in both the product market and the capital markets using a range of measures such as firm size, advertising expenses, analyst coverage and the breadth of ownership in its stock and bonds. Our main finding is that bonds of highly visible issuers enjoy greater liquidity. After controlling for the effects from other determinants of bond liquidity, visibility of the issuing firm is significant in explaining the cross-sectional differences in bond liquidity. Our results are robust to alternative measures of liquidity and different model specifications. Further, bond liquidity improves once its issuer was added to the S&P 500 index. This finding alleviates the concern that the positive relationship between bond liquidity and issuing firm visibility documented in our cross-sectional tests simply reflects the common influence from some omitted variables.

Our study shows that the benefits of firm visibility for bonds can be much greater than what has been documented for stocks. In fact, liquidity has been one of the biggest concerns for bond traders. Recent studies have shown that liquidity affects bond yields and returns in the form of both transaction costs and a risk factor. While early studies have explored the determination of corporate bond liquidity by focusing on bond characteristics such as age and issue size, our findings highlight the importance of firm characteristics in understanding the cross-sectional variations in bond liquidity. To the extent that liquidity is priced in the bond market, our paper suggests that financial polices aiming at improving visibility might also benefit the firm in terms of cost of raising debt.

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**Table 1. Summary statistics of bond characteristics**

This table provides summary information on the characteristics of the 5,635 bonds in our sample. Data on bond characteristics are retrieved from the Mergent FISD database. Panel A presents summary statistics on basic bond characteristics, including issue size, coupon rate, age (number of years since issuance), and time to maturity (in years). Panel B includes information on the percentage of bonds that are rated investment-grade, and that have some complexity features. We also present information on industry classifications.

Panel A: Basic bond characteristics:



Panel B: Other bond characteristics:



**Table 2. Summary statistics on visibility and liquidity measures**

Panel A presents summary statistics for each of the following five measures of visibility: SIZE (book value of debt plus market value of equity), XAD (advertising expenses), NEQUITY (number of mutual funds holding the issuer’s equity), and NANALYST (number of analyst following the firm). SIZE and XAD are based on annual data from Compustat. NEQUITY and NANALYST are calculated using data from Thomson 13f Filings and I/B/E/S, respectively. Correlations between these visibility measures are presented in Panel B. Panels C and D present the summary statistics and correlations for liquidity measures: ZEROPCT (percentage of days in a quarter with zero returns), NTRADES (total number of trades in a quarter), VOLUME (total par value of trading in a quarter), GAMMA (γ in Bao, Pan and Wang (2011)), and AMIHUD (Amihud illiquidity in Amihud (2002)). All the liquidity measures are calculated using bond transaction data from TRACE for the period of 2003 to 2008.

Panel A: Summary statistics on visibility measures



Panel B: Correlations among visibility measures



Panel C: Summary statistics on liquidity measures



Panel D: Correlations among liquidity measures



**Table 3. Univariate analysis of the impact of firm visibility on bond liquidity**

In each panel we form four groups of bonds with increasing visibility, with group 4 including the most visible bonds. The four visibility measures used to sort bonds are SIZE (book value of debt plus market value of equity), XAD (advertising expenses), NEQUITY (number of mutual funds holding the issuer’s equity), and NANALYST (number of analysts following). The reported values in the table are the mean and median values of liquidity for each group. The reported p-values are for the t-test on the difference in mean and the Wilcoxon test on the difference in median between groups 1 and 4. Panel A reports the results using ZEROPCT (percentage of days in a quarter with zero returns) as a liquidity measure. Similarly, Panels B to E report the results with the other liquidity measures, i.e., NTRADES (total number of trades), VOLUME (total par value of trading), GAMMA (γ in Bao, Pan and Wang (2011)), and AMIHUD (Amihud illiquidity in Amihud (2002)). Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively.



**Table 4. Multi-variate analysis of the impact of firm visibility on bond liquidity**

This table examines whether firm visibility affects bond liquidity in cross section by using Fama-MacBeth (1973) regression:



where Liquidity is measured using ZEROPCT. Standard errors are adjusted using the Newey-West procedure. Four alternative visibility measures are used: firm size (SIZE), advertising expenses (XAD), the number of institutions holding equity (NEQUITY), and the number of analysts following the firm (NANALYST). The control variables include bond and firm characteristics. DAMOUNT is the logarithm of the amount of bonds outstanding. BaboveDum is a dummy taking the vaue of one if credit rating is BB or B. BBBdum (CCCbelowDum) is a dummy taking the value of one if the credit rating is above (below) BBB (CCC). TTM is time to maturity. UtilityDum (FinanceDum) is a dummy that takes the value one if the issuer is a Utility (Finance) firm. Also included are the following dummy variables to capture bond features: embedded call or put options (OptionDum), convertibility (ConvertibleDum), sinking fund provisions (SinkFundDum), global offerings (GlobalDum), covenant (CovenantDum), and variable coupon (VarcouponDum). ABSSTKRET is the absolute stock return, and STKTURNOVER is the volume of stock traded. Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively.



**Table 5. Impact of firm visibility on bond liquidity: alternative liquidity measures**

This table performs the same analysis as in Table 4 by replacing ZEROPCT with four other liquidity measures: NTRADES, VOLUME, GAMMA and AMIHUD. Please see Table 2 for definitions of liquidity measures and Table 4 for all other details. For brevity, we omit the coefficients of all control variables. Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively. 

**Table 6. Alternative model specification**

This table estimates a pooled version of regression (1), where the dependent variable is liquidity as measured by ZEROPCT or the fraction of zero returns in the quarter. The main variables of interest are the four measures of visibility: Firm size (SIZE), advertising expenses (XAD), the number of institutions holding the firm’s equity (NEQUITY), and the number of analysts following the firm (NALSYST). All the control variables are defined as in Table 4. Also included are three macro-economic variables: the 10-year Treasury bond return (ABST10YRET), return on the S&P 500 index (ABSSP500RET), and Moody’s corporate credit spreads between Baa and Aaa bonds (BAA\_AAA). Standard errors are corrected to account for potential correlations across bonds and over time as in Thomson (2009). Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively.



**Table 7. Visibility impact by bond credit rating categories**

This table performs the same analysis as in Table 4 separately for investment grade bonds (Panel A) and high-yield bonds (Panel B). The dependent variable is ZEROPCT, the fraction of days within a quarter with zero returns. Four visibility measures are used: firm size (SIZE), advertising expenses (XAD), the number of institutions holding equity (NEQUITY), and the number of analysts following the firm (NANALYST). Coefficients for all control variables are omitted for brevity. Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively.



**Table 8. Visibility in the bond markets**

This table augments the analysis in Table 4 with one additional visibility measure: the number of institutions that hold bonds issued by the firm (NBONDS). All the other variables are defined as in Table 4. Coefficients for all control variables are omitted for brevity. Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively.



**Table 9. Changes in bond liquidity for firms added to the S&P 500 index**

This table examines the changes in liquidity of bonds issued by firms that were added to the S&P 500 index over the period of 2003 to 2010. Pre- and Post-Addition refer to the quarter before and after the quarter during which the company was added to the S&P 500 index. We present both the mean and the median of liquidity in the Pre- and Post-Addition periods. We also report the p-values for the t-test (difference between means) and the Wilcoxon tests (difference between medians). We examine three liquidity measures: ZEROPCT, NTRADES and VOLUME. We examine both the raw liquidity measures and the control-adjusted measures, the latter of which are obtained by subtracting the mean of the control group from that of the S&P 500 index addition sample. The control group consists of all bonds having the same credit rating and similar time to maturity as the bond issued by the firm being added to the S&P 500 index. In each case, we also report results for subsamples of investment grade and high-yield grade bonds. Superscripts a, b, and c denote the significance level of 1%, 5%, and 10%, respectively.



1. Oliver Chang, Simi Kedia and Xing Zhou are at Rutgers Business School, Rutgers University. Jason Wei is at Rotman School of Management, University of Toronto. We gratefully acknowledge the financial support from the Whitcomb Center and the Social Sciences and Humanities Research Council of Canada. [↑](#footnote-ref-1)
2. See “Transparency a Risk for Corp Bond Liquidity – Survey,” Rueters News, 7 June, 2010. Arthur Levitt’s speech titled “The Importance of Transparency in America’s Debt Market,” delivered on September 9, 1998, can be found at <http://www.sec.gov/news/speech/speecharchive/1998/spch218.htm>. [↑](#footnote-ref-2)
3. The breadth of institutional ownership has been used in the prior literature to capture investor recognition and visibility in the equity markets. See, e.g., Kadlec and McConnell (1994), Grullon, Kanatas and Weston (2004), Lehavy and Sloan (2008), and Bodnaruk and Ostberg (2009). [↑](#footnote-ref-3)
4. The economic impact was the smallest when we use the number of analysts as the measure of visibility. But even there, a move from the first to the third quartile is associated with a 6% increase in liquidity measured as the percentage of zero returns. [↑](#footnote-ref-4)
5. Related to the effect of visibility on stock liquidity is the literature that examines the impact of visibility on stock returns. Merton (1987) models this link and shows that higher investor recognition leads to higher prices and lower equilibrium stock returns. Several studies, most recently Bodnaruk and Ostberg (2010), provide empirical support for Merton's predictions. [↑](#footnote-ref-5)
6. Following Grullon, Kanatas and Weston (2004), we use the total dollars spent on advertising instead of the ratio of advertising expenditure to assets or sales. As argued by Grullon, Kanatas and Weston (2004), the purpose is to capture the exposure of the firm to a wide population of investors, not the relative intensity of advertising to assets or sales. [↑](#footnote-ref-6)
7. For block trades, exact size information is not available in TRACE. For investment-grade/high-yield issues, trades greater than $5million/$1million are coded as ‘5MM+’/’1MM+’. When calculating the VOLUME measure, we treat trades with “5MM+”/“1MM+” codes as if their trade sizes were $5,000,000/$1,000,000. [↑](#footnote-ref-7)
8. See for example, Alexander, Edwards, and Ferri (2000), Hong and Warga (2000), Schultz (2001), Chakravarty and Sarkar (2003), Edwards, Harris and Piwowar (2007), Hotchkiss and Jostova (2007), Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008), and Bao, Pan and Wang (2011). [↑](#footnote-ref-8)
9. This setup allows us to capture potential nonlinear effect of credit rating on liquidity. This is similar to Edwards, Harris and Piwowar (2007) who study the cross-sectional determinants of bond transaction costs. Nevertheless, we have also performed the analysis with a numerical rating variable with 1, 2, …, etc corresponding to AAA, AA, …, and so on. The results are qualitatively the same. [↑](#footnote-ref-9)
10. As these are Fama-Mcbeth results we estimate the average Q1 and Q3 for all the quarters. The mean value of ZEROPCT used for this calculation is 0.6722 and is the mean across all the quarters. [↑](#footnote-ref-10)
11. The sample size drops in Panels C and D of Table 5 due to the restrictions imposed in the estimation of GAMMA and AMIHUD measures. [↑](#footnote-ref-11)
12. For funds that are co-managed, the holdings of that fund appear multiple times in the Lipper database. We exclude the duplicates when calculating the aggregate holding. [↑](#footnote-ref-12)
13. The results in Table 8 are based on the liquidity measure ZEROPCT. We have estimated models with other liquidity measures and obtained qualitatively similar results, which are omitted for brevity. [↑](#footnote-ref-13)
14. We also conduct the tests with both bond and firm visibility measures on the investment-grade and high-yield subsamples separately. We continue to find significant impact of both visibility measures for the two groups of bonds. [↑](#footnote-ref-14)
15. Certain bonds didn’t trade in the quarters around the announcement, causing difficulty in estimating/calculating the last two liquidity measures, GAMMA and AMIHUD. We therefore do not report results for these measures. [↑](#footnote-ref-15)