The Value of Attention Grabbing: The Case of Advertising and Corporate Bonds

by

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Abstract

Enhanced visibility -a salient feature of product market advertising- enables a firm to attract new investors, thus benefiting the firm through a capital market channel. The tangible impact of advertising, however, comes from its effect on revenues. To see how investors value salient attributes, we examine how enhanced visibility (i.e., advertising scale) and sales-advertising sensitivity affect corporate bond yields and liquidity. We find that although large advertising expenditures improve bond liquidity, they do not lower credit spreads significantly. However, greater sales-advertising sensitivity widens credit spreads and reduces bond liquidity. Salient attributes thus may have little or no value for bond investors.

JEL classification: M37; G30; G32

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I. Introduction

"Attention is a scarce resource" (Barber and Odean 2008, p. 785) and thus among "many alternatives, options that attract attention are more likely to be considered, hence more likely to be chosen." This is no truer than for stocks among which "familiarity breeds investments."[4] Firms can thus attempt to attract new investors through advertising. Increased attention due to larger advertising expenditures benefits firms with more institutional investors and better stock liquidity (Grullon, Kanatas, and Weston, 2004), greater trading volume, more analyst coverage, and improved stock returns (Chemmanur and Yan 2008).[5]

However, as Barber and Odean (2008) point out, attention can only lead to the optimal choice when salient attributes of the chosen alternative are critical to the investor's utility. Not all investors derive utility from salient attributes. Professional investors, for instance, with disciplined strategies and greater resources to implement them, may be less prone to salient attributes of attention-grabbing events such as news, unusual trading volume, and extreme returns. This then leaves unclear as to how pertinently do investors, particularly institutions, view the attention-grabbing, visibility-enhancing, salient attributes of corporate actions such as advertising? Given that product market advertising is mainly intended for its positive economic

[4]Huberman (2001) coins the phrase "familiarity breeds investments." He shows that Regional Bell Operating Companies' shareholders tend to live in the areas that these companies serve. He sees this as "compelling evidence that people invest in the familiar." Odean (1999) proposes that investors manage the daunting task of choosing among thousands of possible stock purchases by narrowing their search to stocks that recently caught their attention. A large body of evidence supports this notion. For instance, Grinblatt and Keloharju (2001) and Huberman (2001) find that investors tend to concentrate their portfolio strategies on local firms. Coval and Moskowitz (1999) find that portfolio managers tend to invest in locally headquartered firms. Evidence also suggests that widespread public dissemination of previously known information by a third party can also lead to price appreciation. Huberman and Regev (2001) show that subsequent to being featured in the Sunday edition of the *New York Times* for a cancer drug discovery, EntreMed experienced unpredicted appreciation in stock price. This was, however, barely "news" since this breakthrough in cancer drug research was reported in *Nature* more than five months earlier.

[5]A growing body of literature in marketing (e.g., Joshi and Hanssens 2004; Cheng and Chen 1997; Chauvin and Hirschey 1993; Rao, Agarwal, and Dahlhoff 2004; among others) also suggests that advertising positively relates to corporate value. Keller (2002) attributes brand equity related augmented cash flows to customer loyalty, increased marketing efficiency, brand extensions, and higher profit margins. Similarly, while Farquhar (1989) suggests that advertising-related cash flow augmentations may be traceable to price premiums, Boulding, Lee, and Staelin (1994) relate increased cash flows to capturing greater market share.

consequences (Stigler 1961; Telser 1964; Milgrom and Roberts 1986), then it is critical to distinguish the impact of salient attributes of advertising from the tangible, real effects of advertising. To address this question we examine how enhanced visibility -the salient feature of large advertising expenditures- and sales-advertising sensitivity -the tangible feature of advertising- relate to the cost of corporate debt.

We choose corporate bonds for a variety of reasons. In contrast with equity holders, corporate bonds are relatively illiquid.[6] Bondholders may find potential increased liquidity that follows the increased visibility obtained by larger advertising expenditures attractive.[7] However, bondholders -mostly insurance companies and pension funds- are professional investors with specific investment guidelines. Enhanced visibility thus may have little effect on them. Bondholders' returns are highly dependent on interest payments and hence the borrower's ability to make good on contractual payments becomes the first order of concern.[8] Any activity that could deteriorate the financial health and stability of the borrower's income stream would be deemed detrimental. Since advertising expenditures occur before debt service, they limit the firm's ability to meet debt obligations, thereby increasing default probability and corporate bond

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[6] Sarig and Warga (1989) show that after the initial offering phase, the corporate bond market becomes quite illiquid mainly because the buyers tend to hold the instruments for a long time.

[7] Advertising for the sake of attracting bond investors is not uncommon. Anecdotal evidence can be found in an article titled "E*Trade Sweetens Offering To Get Investors on Board," McGee and Buckman report that "E*Trade Group Inc. may have sponsored the Super Bowl's half-time show, but apparently not too many convertible bond investors were watching. Despite a weeklong road show, investors balked at the terms originally proposed by E*Trade and its underwriter FleetBoston Financial Corp.'s Robertson Stephens for the $500 million offering. By the time the firm sat down to discuss final pricing yesterday evening, it appeared as though E*Trade would be paying a higher interest rate. The company also had to offer more generous conversion terms to convince investors to subscribe for the full deal…." in "Deals & Deal Makers: E*Trade Sweetens Offering To Get Investors on Board" by Suzanne McGee and Rebecca Buckman, *The Wall Street Journal*, February 2nd, 2000.

[8] Elton, et al. (2001) state that corporate bonds' credit spreads reflect three important factors: expected default, personal taxes, and a systematic risk premium. For instance, for an A-rated, 10-year bond, they find that about 18% and 47% of the credit spreads is due to default risk and taxes, respectively. Of the remaining spread, as much as 85% is explained by the Fama-French risk factors, leaving little room for all other factors, including liquidity. Interestingly, they also find that the proportional contribution of default risk to the credit spread grows exponentially with credit ratings. For instance, for a 10-year, BBB-rated bond, the percentage contribution of the default risk rises to 41%.

yields. Moreover, advertising campaigns can also be seen as risky gambles with significant potential for wealth transfer from bondholders to stockholders (Myers 1977). The real economic impact of advertising, i.e., sales-advertising sensitivity, should matter greatly for bondholders.

Using a large panel of plain vanilla corporate bonds from U.S. nonfinancial firms over the period from January 1994 to December 2006, we examine the impact of adverting on credit spreads and liquidity. We find that while increased visibility (as measured by larger advertising expenditures[9]) narrows credit spreads, albeit statistically insignificantly, greater sales-advertising sensitivity significantly and pronouncedly widens the credit spreads. Interestingly, we find that much like equities (see Grullon, et al. 2004), greater visibility increases the liquidity of corporate bonds. However, greater sales-advertising sensitivity leads to significantly lower corporate bond liquidity. Our results indicate that while bondholders may marginally value the salient attributes (i.e., enhanced visibility) of borrowers' advertising campaigns, they strongly care about their real economic impact of advertising.

Our results are consistent with Barber and Odean (2008), who posit that professional investors are less likely to be affected by attention grabbing. Corporate bond investors do not seem to be favorably viewing advertising exclusively aimed at grabbing their attention. More importantly, our results indicate that bondholders abhor the riskiness of embedded real options in advertising. Since the economic impact of advertising on sales is uncertain, advertising contains a significant real option component that mostly benefits residual claimants, and perhaps at the expense of a wealth transfer from bondholders (Myers 1977). As Leland (1998) shows,

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[9] Grullon, et al. (2004) use advertising expenditures as a proxy for the degree of visibility. Citing Bagwell's (2001) survey of the economics of advertising, they argue that although "… advertising is presumably aimed at increasing the firm's market share in the product market, at the minimum it should make the firm's name and products better known to both consumers and investors…" (p. 440). Indeed, Grullon et al. (2004) find results consistent with the idea that more advertising can increase the advertising firm's stock market liquidity and institutional ownership.

corporate bond prices are severely, adversely impacted by the agency costs of overinvestment, which are prototypical in advertising.

Our analysis also extends recent studies on the impact of familiarity on asset returns (Coval and Moskowitz 1999; Grinblatt and Keloharju 2001; Huberman 2001; Grullon, et al. 2004; Chemmanur and Yan 2008). Building on work by Grullon et al. (2004), we show that as in equities, the advertising scale improves the liquidity of corporate bonds. Interestingly, gains made from increased advertising (in terms of lower credit spreads or greater liquidity) are not enough to offset the losses due to increased spread/lower liquidity if revenues are highly sensitive to advertising. Firms cannot simply reduce their borrowing cost by ramping up their advertising. In fact, for firms with high sales-advertising sensitivities, any increase in advertising expenditures will result in unfavorable borrowing conditions. Gains resulting from better stock and bond liquidity should be taken with a grain of salt because *a priori* the net effect of increasing advertising on the total firm value is unclear.

Our findings also shed additional light on the economics of advertising. Economic theorists contend that advertising provides valuable product market information that can help the firm to signal quality more credibly and compete more effectively (Stigler 1961; Telser 1964; Milgrom and Roberts 1986; Bagwell and Ramey 1994; Chemmanur and Yan 2009). Our results based on the corporate bond market highlight the greater relative import of the real economic impact of advertising as compared to the capital market effects of advertising. While trading liquidity is positively affected by larger advertising, the net wealth effect of large advertising expenditures is mainly driven by the real economic impacts of advertising, i.e., the sales-advertising sensitivity.

The rest of this paper is organized as follows. Section II describes sample selection and the data. In Sections III and IV, we discuss our empirical methodologies and present the results. In

Section V, we offer some robustness checks, and finally in Section VI we present our conclusions.

II. Sample Selection, Variable Description, and Summary Statistics

A. Sample Selection

To construct our sample of potential corporate bonds, we start with all bonds issued by U.S. firms that can be identified in the Fixed Income Database (FISD), as provided via WRDS, for the period of 1994 to 2006. Our main focus is on bond transactions as reported by FISD.[10] As is the convention of previous research, we ensure that payout characteristics of the bonds in our sample are similar; hence we exclude all bonds with option-like features such as callability, putability, convertibility, and sinking fund provisions. Additionally, we exclude zero-coupon and floating-rate bonds. We also delete bonds without ratings by either Standard & Poors (S&P) or Moody's. Similar to previous bond pricing studies (see, e.g., Collin-Dufresne et al. 2001; Eom, Helwege, and Huang 2004), we exclude regulated industries (i.e., financial services and utilities).

Next, we merge the data with Treasury term structure information from the Board of Governors of the Federal Reserve. We then find the average characteristic of each transaction per firm per month. We merge our data with data from monthly CRSP and OptionMetrics. We use monthly CRSP to obtain stock prices, stock return volatility, and market volatility. We use OptionMetrics to obtain the probability of return jump implied by the S&P500 Index options. We only keep those firms that have two years of valid stock returns. We use the COMPUSTAT annual database to obtain accounting information such as leverage, interest coverage, quick ratio, profitability, earnings volatility, and earnings management (accruals). We require our firms to have valid accounting measures in the year prior to transaction. Some of the accounting

[10]Other studies by, for example, Elton et al. (2001); Eom, Helwege, and Huang (2004); Gebhardt, Hvidkjaer, and Swaminathan (2005); and Guntay and Hackbarth (2007) also rely on the Fixed Income Database.

characteristics, however, are multi-year averages. In general, for a firm to be considered, accounting information must be available for three years prior to transactions. To avoid biases due to outliers, all of our accounting characteristics are winsorized at the 2% level (i.e., observations are trimmed at the 1% level at both tails). After merging our transaction data with COMPUSTAT and deleting firms that do not have valid advertising expenses for either the current or previous years, we have a final sample of 27,792 firm-month observations.

B. Variable Definitions

1. Dependent Variables: Credit Spread and Liquidity

For our purposes, the credit spread is computed as the difference between the corporate bond yield and the fitted yield on an otherwise equivalent Treasury bond. Following Duffee (1998), Collin-Dufresne et al. (2001), and Guntay and Hackbarth (2010), we use a linear interpolation scheme for the Treasury yield rates reported by the Federal Reserve Board of Governors (H.15 release of the Federal Reserve System) for maturities of 1, 2, 3, 5, 7, 10, 20, and 30 years to approximate the entire yield curve. Since yields on only the aforementioned bonds are available from the Fed, we use interpolation to find the Treasury yield curve for every maturity. We then define the credit spread (CSPRD) as the difference between the reported yield-to-maturity of the corporate bond and the corresponding Treasury yield.[11]

Recent work indicates that liquidity is a priced risk in the yields of corporate bonds (Chen et al. 2007; Covitz and Downing 2007). Following recent studies (Chen et al. 2007; Covitz and Downing 2007), we use a host of proxies for bond liquidity. Following Guntay and Hackbarth (2010), we use fractional trading months (PROPLIQ) as the proxy for corporate bond liquidity.

[11]Although other more sophisticated methods can be used to find the fitted Treasury yield curve, Elton et al. (2001) note that these different proxies yield qualitatively similar results. As a result, we use the simple interpolated fitted Treasury yields for the analysis pursued in the paper.

The fractional trading months (PROPLIQ) is a bond-level proxy for liquidity that counts the number of months a bond has a market quote during the past 12 months divided by 12.

2. Test Variables: Advertising Scale and Sales-Advertising Sensitivity

We assess the influence of advertising on cost of debt by studying two distinct dimensions -scale and sales' sensitivity- of advertising campaigns. First, as in Grullon et al. (2004), we assume that the scale of advertisement captures the total visibility impact of advertising. The basic intuition here is that "… while such advertising is presumably aimed at increasing firm's market share in the product market, at a minimum it should make the firm's name and products better known to both consumers and investors" (Grullen et al. 2004, p. 440). Following Grullon et al. (2004), we proxy the visibility impact of advertising by its scale measured as the natural log of a firm's advertising expenditures. We use the natural log of the current fiscal year's advertising expenditures (LOGADV0) as a proxy for the visibility. To control for the industry effects, we normalize our variables as follows:

$$n\mathrm{LOGADV0}_{i,t} = \frac{\mathrm{LOGADV0}_{i,t} - \min\limits_{i \in \text{2digit SIC}}\{\mathrm{LOGADV0}_{i,t}\}}{\max\limits_{i \in \text{2digit SIC}}\{\mathrm{LOGADV0}_{i,t}\} - \min\limits_{i \in \text{2digit SIC}}\{\mathrm{LOGADV0}_{i,t}\}}$$

Verma (1980) shows that from a price theoretic approach -where consumers maximize their utilities net of information costs and advertising helps to reduce these costs- the sales-advertising relationship is highly nonlinear and complex. When firms face uncertain sales, such nonlinearities are further complicated by the firm's risk aversion (Nguyen 1987). Linear approximations of such sales-advertising relationships take the form of time series regressions whereby sales levels are related to both past sales and past advertising levels. Intuitively then, we can define the sales-advertising sensitivity in terms of the degree to which past levels of advertising outlays determine current levels of sales. For instance, Depken and Wilson (2004) use time series regression coefficient estimates to arrive at the imputed value of the advertising elasticity of magazine subscriptions. However, given the limited number of time series observations on firm-level advertising expenses in the COMPUSTAT database, estimating such time series models can prove to be difficult. We thus use a variable that closely mimics the notion of elasticity while allowing us to circumvent the data limitations. We measure the sales-advertising sensitivity (eA2S5) as the five-year correlation between lagged log advertising expenditure and current log sales, or for firm *i* at time *t*:

$$\mathrm{eA2S5}_t = \frac{\frac{1}{5}\sum_{k=0}^{4}\left[\log(\mathrm{Adv}_{t-1-k}) - \frac{1}{5}\sum_{j=0}^{4}\log(\mathrm{Adv}_{t-1-j})\right]\left[\log(\mathrm{Sales}_{t-k}) - \frac{1}{5}\sum_{j=0}^{4}\log(\mathrm{Sales}_{t-j})\right]}{\left(\sum_{k=0}^{4}\left[\log(\mathrm{Adv}_{t-1-k}) - \frac{1}{5}\sum_{j=0}^{4}\log(\mathrm{Adv}_{t-1-j})\right]^2 \sum_{k=0}^{4}\left[\log(\mathrm{Sales}_{t-k}) - \frac{1}{5}\sum_{j=0}^{4}\log(\mathrm{Sales}_{t-j})\right]^2\right)^{\frac{1}{2}}}.$$

To account for industry variations, we normalize our sales-advertising variable as follows:

$$\mathrm{neA2S5}_{i,t} = \frac{\mathrm{eA2S5}_{i,t} - \min\limits_{i\,\in\,\text{2digit SIC}}\{\mathrm{eA2S5}_{i,t}\}}{\max\limits_{i\,\in\,\text{2digit SIC}}\{\mathrm{eA2S5}_{i,t}\} - \min\limits_{i\,\in\,\text{2digit SIC}}\{\mathrm{eA2S5}_{i,t}\}}.$$

3. Control Variables

We include several control variables to ensure that the known determinants of credit spreads and bond liquidity do not confound the influence of our test variables. The choice of control variables follows Elton et al. (2001), Collin-Dufresne et al. (2001), Campbell and Taksler (2003), Chen et al. (2007), and Guntay and Hackbarth (2010). Given that firms with higher default probability and/or lower expected recovery rates are expected to have higher credit spreads, we control for several macroeconomic, bond-specific, and firm-specific proxies for common default and recovery risk factors. Table 1 provides the list of all variables with brief descriptions. The main control variables are defined as follows.

Credit rating. As in Collin-Dufresne et al. (2001) and Chen et al. (2007), we control for credit rating (CRD) as a possible determinant of credit spreads. We utilize COMPUSTAT's numerical equivalent of an average of Moody's and S&P's credit rating. As measured, a higher numeric value reflects greater risk and is expected to relate positively to credit spreads.

Treasury term structure. In structural models of credit risk, a rise in the spot rate effectively reduces the likelihood of default (Leland 1994; Longstaff and Schwartz 1995). Previous empirical studies (Duffee 1998; Chen et al. 2007) indicate that credit spreads tend to fall when Treasury yields rise. To control for variations in the risk free rate, we include the one-year Treasury bill yield (LEVEL) in our credit spread model. Litterman and Scheinkman (1991) show that the term structures of Treasury rates have explanatory power in predicting both the interest rate movements and macroeconomic growth. Ju and Ou-Yang (2006) show that as the yield curve becomes steeper, credit spreads widen. We control for the term structure influence on credit spreads by including the difference in the yield on ten-year and two-year constant maturity Treasury instruments (SLOPE). As in Chen et al. (2007), we use the spread between the three-month Euro-dollar rate and the three-month Treasury bill yield (EUROD) to capture the Treasury bonds' "crowding out" adverse liquidity effect.

Bond Maturity and Age. Merton (1974) shows that credit spreads and maturity are nonlinearly related. Helwege and Turner (1999), however, find that on average, the term structure of credit spreads is upward-sloping. We include the natural log of the maturity of a bond (LogMAT) to control for the credit spread of term structure. Time since the issuance of a bond has been shown to relate positively to credit spreads (see Warga 1992; Perraudin and Taylor 2004; Yu 2005). Generally speaking, the older a bond becomes, the less often it will transact, leading to a higher spread. To control for the effects of the age of a bond, we include log of bond age (LogAGE) defined as the log of the number of years elapsed between the settlement and the issuance dates.

Volatility. Structural models also predict that the volatility of firm value is positively related to credit spreads (see Leland 1994; Longstaff and Schwartz 1995; and Acharya and Carpenter 2002). We utilize equity volatility (RETVOL) to control for volatility in firm value. Specifically, we define RETVOL as the annualized standard deviation of the firm's monthly stock returns over the preceding 24 months. Earnings volatility poses significant risk for debt holders and hence is reflected in credit spreads. We control for historical earnings volatility (VOLEARN) measured as the five-year standard deviation of ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to assets. Chen et al. (2007) show that corporate bonds with more volatile yields tend to have less liquidity. To control for the influence of yield volatility on bond liquidity, we include the rolling 12-month standard deviation of the bond's yield-to-maturity (YldVol) in our liquidity model.

Leverage. Default risk is directly related to the amount of debt outstanding. Following Chen et al. (2007), we use the ratio of a firm's book value of total liabilities to its market value of equity (TD2Cap). We also use the ratio of long-term debt to total assets (LTDB).

Debt Servicing Ability. Firms with higher operating income can meet debt service obligations more easily and hence are less likely to default in the near future. As in Guntay and Hackbarth (2010), we use the ratio of earnings before tax and depreciation divided by book value of total assets to control for profitability as a determinant of credit spread. A firm's ability to meet debt obligations is directly related to its liquid assets. We use the ratio of cash and receivables to total assets as a measure of asset liquidity influencing credit spreads. The ability to meet periodic debt service is the first test in determining whether a borrower has not defaulted. Following Chen et al. (2007), we measure the incremental influence of the pre-tax coverage using four censored variables constructed per the procedure outlined in Blume, Lim, and MacKinlay (1998).[12]

Firm Size. Chen et al. (2007) show that larger firms' bonds tend to have better implied liquidity and smaller bid-ask spreads. We use the log of firm size (SIZE) -defined as the sum of its market value of equity and book value of debt- as a control. Since larger firms tend to have larger equity trading volume, we also use the natural log of the firm's past 12 months cumulative trading volume (LogEVolm).

C. Summary Statistics

Table 1 provides summary descriptive statistics for the variables analyzed. The mean credit spread for our sample bonds is 2.191%. The mean three-month T-bill yield (LEVEL) is 3.545%, and the mean difference between 30-year T-bond and three-month T-bill yields (SLOPE) is 1.102%. Duffee (1998) shows that on average credit spreads are between 0.67% and 1.42%, centered at 1.01% for medium-term A-rated bonds. Elton et al. (2001) show that credit spreads of industrial firms range from 0.392% to 1.349% over the period of 1987 to 1996. They also report that the corresponding Treasury yields range from 5.265% to 8.382%. Firms in our sample have larger credit spreads than those documented previously. The difference may be reflective of the unique time frame of our sample. Our sample extends over the period between 2000 and 2004 when the collapse of corporate icons like Enron led to historically high credit spreads. At the same time, the Federal Reserve's efforts to combat the economic slowdown caused Treasury yields to fall to historically low levels. Firms in our sample have a mean size of

[12] These four censored variables reflect whether a firm's five-year interest coverage is lower than 5%, 10%, 20% or not. All censored variables are initially set to zero. For firms with the five-year average interest coverage ratio of less than 5%, the first censored variable takes on the value of average interest coverage. For firms with the five-year average interest coverage ratio of more than 5% but less than 10%, the second censored variable takes on the value of average interest coverage minus 5%. For firms with the five-year average interest coverage ratio of more than 10% but less than 20%, the third censored variable takes on the value of average interest coverage minus 10%. For all other firms, the fourth censored variable takes on the value of average interest coverage minus 20%.

about $17 billion USD and generate an average EBITDA return on assets of around 14.5%. The mean long-term debt ratio for our sample firms is about 37%, which is comparable to those reported in previous studies. Overall, firms in our sample are large and profitable industrial firms with relatively low leverage. Our sample average bonds have 11.408 years-to-maturity and are 3.605 years old. Comparable to the samples in previous empirical studies (see Collin-Dufresne et al. 2001; Guntay and Hackbarth 2010), our sample bonds on average trade one month per year.

[Insert Table 1 here.]

III. Impact of Advertising Scale and Sales-Advertising Sensitivity on Credit Spreads

A. Univariate Results

To provide preliminary insights into the relationship between credit spreads and advertising, we plot the credit spread of each bond versus the firm's advertising visibility (scale) and versus the sales-advertising sensitivity in Figure 1. Panel A depicts the relation between credit spreads and advertising visibility, nLOGADV0, while panel B shows the distribution of credit spreads across two levels of the advertising-sales sensitivity, neA2S5. The Figure shows that large advertisers and firms with low sales-advertising sensitivity have lower average credit spreads and tighter credit spread distributions.

[Insert Figure 1 here.]

Table 2 provides a comparison of the credit spreads across ratings, maturities, firm sizes, and leverage levels. Larger scale advertisers, i.e., firms with greater visibility, have consistently smaller spreads across various maturity, size, and leverage categories. The relationship between advertising visibility and spread, however, is not consistent in sign or significance across ratings. Interestingly, highly levered, relatively smaller firms and firms with shorter-term bonds seem to gain more from the increased visibility. For instance, large-scale advertising firms in the highest leverage categories have an average credit spread that is less than half of their counterparts in the small-scale advertising group. With respect to sales-advertising sensitivity, in general, firms with low sensitivity have statistically significantly lower credit spreads. The gap between the high and low sensitivity firms' spreads widens almost monotonically with deteriorating credit quality. Further, low sensitivity advertisers with longer-term debt, larger firm size, and lower leverage, in particular, have smaller spreads. For instance, while on average low sensitivity advertisers' credit spreads are lower by almost 10 basis points, large firms with low sales-advertising sensitivity have a 42 basis point credit spread advantage over their high sensitivity counterparts. In sum, our univariate results suggest that greater visibility and less sensitivity may narrow credit spreads.

[Insert Table 2 here.]

B. Multivariate Results

To analyze the impacts of advertising scale and sales-advertising sensitivity on corporate bond credit spreads in a multivariate regression framework, we first use a reduced form panel regression model[13] described below:

$$\text{CSPRD}_{b,i,t} = \alpha + \beta_1 \text{VISIBILITY}_{i,t} + \beta_2 \text{SENSITIVITY}_{i,t} + \mathbf{B}_{b,i,t}\mathbf{X}_{b,i,t} + \varepsilon_{b,i,t} \tag{1}$$

where the dependent variable ($\text{CSPRD}_{b,i,t}$) is the credit spread on bond *b* of firm *i* at time *t*; $\text{VISIBILITY}_{i,t}$ is our proxy of advertising visibility for firm *i* at time *t*; and $\text{SENSITIVITY}_{,t}$ is our proxy of sales-advertising sensitivity for firm *i* at time *t*. The explanatory variables in $X_{b,i,t}$ are controls for macroeconomic conditions, bond-level characteristics, and firm-level attributes.

[13]Current empirical models of credit spreads sidestep direct estimation of any structural equation. Duffee (1998), Elton et al. (2001), Collin-Dufresne et al. (2001), Longstaff et al. (2005), Yu (2005), and most recently Chen et al. (2007) are a few among a growing list of empirical works on credit spread that have utilized the reduced-form empirical modeling of credit spreads to avoid the rigidity and complexity of structural models.

These variables include credit rating (CRD), Treasury bill yield (LEVEL), Treasury term spread (SLOPE), Euro dollar/Treasury bill yield spread (EUROD), the natural log of bond's age (LogAGE), the natural log of years-to-maturity (LogMAT), stock return's volatility (RETVOL), ratio of total debt to capital (TD2Cap), long-term debt to assets ratio (LTDB), earnings volatility (EARNVOL), quick ratio (QUIK), EBITDA to assets ratio (ROA), and four interest coverage dummies per Blume et al. (1998) (INTD1, INTD2, INTD3, and INTD4). As noted before, to check the robustness of our results, we then estimate our baseline model accounting for the year and industry fixed effects. Next, we estimate regressions with Newey-West standard errors. Third, we adopt the Fama-Macbeth approach by estimating cross-sectional regressions for each month and estimating average coefficients. Finally, we estimate cross-sectional regressions based on time-series averages of variables averaged at the bond-level.

We report the results in Table 3. Supportive of our main hypothesis and consistent with the univariate results, the results indicate that credit spreads increase with advertising-sales sensitivity. The regression coefficient on sales-advertising measure (neA2S5) is positive and statistically significant at better than the 10% level of significance. Our measure of visibility (nLOGADV0) does not seem to be statistically significantly related to credit spreads. All our regression models use robust (White 1980, heteroskedasticity adjusted) standard errors corrected for correlation across multiple observations for a given firm. All models have reasonably high explanatory power as indicated by model R-squares that exceed 62% and are comparable to recent research on credit spreads (see, e.g., Klock, Mansi, and Maxwell 2005).

[Insert Table 3 here.]

The coefficients on the sales-advertising sensitivity (neA2S5) is positive and statistically significant at better than the 1% level. Depending on the specification, the magnitude of the coefficient being between 0.424 (panel regression with year and industry fixed effect) and 0.914 (cross-sectional regression) indicates that firms with one-to-one sensitivity face 42 to 91 basis points larger credit spreads than firms with no sensitivity. As mentioned earlier, the advertising scale, as a measure of visibility, does not seem to have a statistically significant impact on credit spreads. This suggests that our univariate results may be confounded by the effects of other determinants of credit spreads and perhaps visibility, per se, is not an important determinant of credit spreads. Our results are robust to the addition of fixed effects and model specification.

All of the control variables, regardless of model specification, behave in a fashion consistent with the evidence reported in previous research. For example, as in Duffee (1998), we find both the Treasury bill yield (LEVEL) and the Treasury term spread (SLOPE) to be negatively related to credit spreads across all empirical specifications. Firms with better credit quality (CRD) have smaller credit spreads and greater liquidity. More profitable (as measured by ROA) firms and firms with better asset liquidity (as measured by QUIK) have smaller credit spreads, while more levered firms (as measured by LTD and TD2Cap) have wider credit spreads. Firms with greater equity risk (as measured by RETVOL and EARNVOL) have larger spreads. Lastly, longer maturity (LogMAT) and older (LogAGE) bonds have wider credit spreads.

C. Advertising and Credit Spreads Across Sub-Samples

A concern with our previous analysis may be that the effect of advertising is confounded by the inherent nonlinearity of the term structure of credit spreads. The extant structural models suggest that the term structure of credit spreads may be nonlinearly related to a firm's credit quality, debt maturity, firm size, and leverage levels. Merton (1974) shows that the shape of the credit spread curve changes with changes in a firm's leverage and earnings volatility. Empirical evidence (see Duffee 1998; and Yu 2005) also indicates that credit spreads and credit quality are linked nonlinearly. To control for these nonlinearities, following Collin-Dufresne et al. (2001) among others, we estimate out baseline regression model separately for firms sorted on credit rating, bond maturity, firm size, and leverage tertiles.

The results are reported in Tables 4. For brevity, we present coefficient estimates of our test variables only. The coefficient estimates for visibility are insignificant. The coefficient estimates of the advertising-sales sensitivity measure are for the most part statistically significant and decrease with firm size while increasing with credit rating and leverage. Our estimates suggest that increasing sensitivity from zero to one increases credit spreads by 29 and 127 basis points for medium (A-BBB) and low (BB and lower) rated firms. A similar rise in sensitivity increases credit spreads by 60 and 46 basis points in small and mid-size firms, respectively. A similar rise in sensitivity increases credit spreads by 74 and 119 basis points in medium and highly levered firms, respectively. Further, the sales-advertising sensitivity appears to be associated with higher credit spreads (statistically significant) in all the maturity categories. The adverse impact of advertising sensitivity on credit spreads is largest in mid-term debt maturity bonds.

[Insert Tables 4 here.]

IV. Impacts of Advertising Scale and Sales-Advertising Sensitivity on Bond Liquidity

A. Univariate Results

We first analyze the relation between bond liquidity and advertising characteristics within a univariate framework. Figure 2 plots bond liquidity (PROPLIQ) versus a firm's advertising scale and sales-advertising sensitivity. Panel A depicts the relation between liquidity and advertising scale for the below and above median advertising scale groups. Panel B shows the distribution of liquidity across two levels of the advertising-sales sensitivity. The figure indicates that large-scale and low sensitivity advertising firms have bonds that are more liquid.

[Insert Figure 2 here.]

Table 5 provides a comparison of two measures of liquidity -the proportion of trading months in the past 12-month period, PROPLIQ, and the natural log of the total volume traded in the past 12 months, LogTVolm- across ratings, maturities, firm sizes, and leverage levels. For the whole sample, larger advertisers as well as low sales-advertising sensitivity firms have greater bond liquidity. Panel A indicates that this pattern generally holds across various credit rating categories except for the lowest credit rating classes. The Panel B results indicate that irrespective of maturity categories, large-scale and low sales sensitivity advertisers have more liquid bonds. In Panel C we report that irrespective of firm size, low sensitivity advertisers have greater liquidity in their bonds. Further, except for the firms in the bottom third firm size categories, the greater scale of advertising relates positively to bond liquidity. Finally, in Panel D we report that except for the most levered tertile, bond liquidity is greater for firms with low sales-advertising sensitivity. Similarly, irrespective of leverage levels, a larger advertising scale relates to greater liquidity of its bonds. In sum, these univariate results suggest that greater visibility related to large-scale advertising and low sales-advertising may contribute to greater liquidity of a firm's bonds.

[Insert Table 5 here.]

B. Multivariate Results

Extending our univariate analysis, we relate advertising characteristics to bond liquidity in a multivariate regression framework. Following recent empirical studies (Covitz and Downing 2007; Chen et al. 2007), we estimate the following reduced-form credit risk model:

$$\text{Liquidity}_{b,i,t} = \delta + \lambda_1 \text{VISIBILITY}_{i,t} + \lambda_2 \text{SENSITIVITY}_{i,t} + \mathbf{\Theta}_{b,i,t} \mathbf{Z}_{b,i,t} + \varsigma_{b,i,t} \qquad (2)$$

where the dependent variable ($\text{Liquidity}_{b,i,t}$) is the liquidity of a corporate bond *b* of firm *i* at time *t*; $\text{VISIBILITY}_{i,t}$ is the normalized natural log of current advertising expenditures (nLOGADV0) for firm *i* at time *t*; and $\text{SENSITIVITY}_{,t}$ is the five-year correlation between lagged advertising and sales (neA2S5) for firm *i* at time *t*. $Z_{b,i,t}$ is a vector of control variables for corporate bond *b* of firm *i* at time *t*. The explanatory variables in $Z_{b,i,t}$ control for macroeconomic conditions, bond-level characteristics, and firm-level attributes. These variables include credit rating (CRD), the natural log of a bond's age (years after issuance) (LogAGE), the natural log of years-to-maturity (LogMAT), firm size (SIZE), trading volume (LogEVolm) of a firm's stock, and bond yield volatility (YldVOL). As noted before, to check the robustness of our results, we then estimate our baseline model accounting for the year and industry fixed effects. Next, we estimate regressions with Newey-West standard errors. Third, we adopt the Fama-Macbeth approach by estimating cross-sectional regressions for each month and estimating average coefficients. Finally, we estimate cross-sectional regressions based on time-series averages of variables averaged at the bond-level.

The results of our multivariate regression analysis presented in Table 6 are largely consistent with our main hypothesis and previously reported univariate results. Bond liquidity is increasing in advertising visibility and decreasing in sales-advertising sensitivity. The regression coefficients on visibility (nLOGADV0) and sensitivity (neA2S5) are, respectively, positive and negative and statistically significant mostly at the better than 1% level. All of our regressions use robust standard errors corrected for correlation across multiple observations for a given firm. Our results are robust to the inclusion of year and industry fixed effects and model specification. All models have explanatory power comparable to that reported by recent research on credit spreads (see, e.g., Covitz and Downing 2007; Chen et al. 2007).

[Insert Tables 6 here.]

Our baseline coefficient on the visibility measure, normalized natural log of the current advertising expenditure (nLOGADV0), is 0.033, indicating that for every percentage point increase in the advertising scale, the average bond trading frequency of one month per year will increase by an additional 2 weeks. The baseline coefficient on our sensitivity measure, namely the normalized five-year correlation between sales and lagged advertising (neA2S5), is -0.045, indicating that by increasing sensitivity from zero to one, the average bond trading frequency of one month per year will increase by an additional 3 weeks.

In terms of control variables, it appears that lower credit quality bonds are more liquid as are bonds of larger firms and firms with greater equity trading volume. While higher yield volatility associates positively with bond liquidity, as expected, bonds are more liquid at either end of their lifecycles.

C. Advertising and Bond Liquidity Across Sub-Samples

To control for possible nonlinearities, we follow the extant literature (e.g., Chen et al. 2007) and estimate our liquidity regression models separately for firm tertiles based on credit rating, bond maturity, firm size, and leverage. In Table 7, our results show that while the visibility helps liquidity only for the lower credit rating firms, the adverse impact of sensitivity is pervasive in all credit quality categories. Irrespective of bond maturity, visibility improves bond liquidity. Greater sensitivity lowers liquidity more so for longer maturity bonds.

In Table 7 the results of a similar analysis for subgroups of firms based on firm size and leverage tertiles are reported. The results indicate that the coefficient estimate of visibility is only statistically significant for small firms, and low and high leverage firms. Except for mid-size and high leverage firms, the coefficient estimates on sensitivity are statistically significant at better than 10% level. The adverse effect of sensitivity increases with firm size and leverage.

[Insert Table 7 here.]

V. Robustness Analyses

As is shown previously, our credit spread and liquidity models are robust to the addition of year and industry fixed effects. Additionally, our Newey-West, Fama-MacBeth, and cross-sectional estimates suggest that our baseline estimates are also robust to model specification and are not affected by the time-series and cross-sectional serial correlations. One remaining concern though is whether the effects of visibility and sensitivity on credit spread and liquidity merely proxy for the interlink between corporate bonds' credit spread and liquidity (see, e.g., Longstaff et al. (2005) and Chen et al. (2007) for details.)

Bond liquidity measures may contain information about credit quality and thus may affect credit spreads through the credit risk channel. Chen et al. (2007, p. 135) argue that "… Under the assumption that much of the liquidity costs are due to adverse selection under asymmetric information … asymmetric information on its credit quality … is the main reason for adverse selection costs. … [H]igher liquidity costs could [then] mean lower credit quality, which could lead, in turn, to higher yield spreads…"

To control for the potential endogeneity problems arising from the possibility that advertising may be simultaneously determining credit spread and liquidity, we employ the following simultaneous equation model of credit spreads and bond liquidity:

$$\begin{aligned}\mathrm{CSPRD}_{b,i,t} &= \alpha' + \eta'\mathrm{Liquidity}_{b,i,t} + \beta_1'\mathrm{VISIBILITY}_{i,t} + \beta_2'\mathrm{SENSITIVITY}_{i,t} \\ &\quad + \mathbf{\Phi}'_{b,i,t}\mathbf{X}_{b,i,t} + \varepsilon'_{b,i,t}\end{aligned}$$

$$\text{Liquidity}_{b,i,t} = \delta' + \mu\text{CSPRD}_{b,i,t} + \lambda_1'\text{VISIBILITY}_{i,t} + \lambda_2'\text{SENSITIVITY}_{i,t} + \mathbf{\Theta}'_{b,i,t}\mathbf{Z}_{b,i,t} + \varsigma'_{b,i,t}$$

The results are presented in Table 8. The estimates indicate that after controlling for potential endogeneity problems, while advertising visibility only marginally affects credit spreads, it significantly contributes to greater liquidity. Further, consistent with the previous results and our main hypothesis, we find that high sales- advertising associates with larger credit spreads and lower bond liquidity. The results are robust across various measures of liquidity. The control variable estimates are broadly consistent with the previously reported results.

[Insert Table 8 here.]

VI. Conclusion

The extant literature suggests that since product market advertising brings about consumer and investor familiarity, advertising can lead to lower equity risk premiums. Although the existing studies support the notion that more familiarity breeds more equity investment, the evidence with respect to bonds is limited at best. We argue that for asset classes such as corporate bonds, for which enhancing familiarity may be significantly costly, the net impact on the risk premium is unclear. We show that for corporate bonds, while greater advertising scale marginally improves credit spreads and liquidity, the product market efficacy of the advertising campaigns may play a more crucial role. Firms that cannot otherwise demonstrate a notable ability to improve sales through advertising may face higher borrowing costs that may far exceed any benefits that they may derive from increased familiarity. In essence, investors treat the embedded signaling value of any corporate action aimed at improving visibility as distinct from pure visibility enhancement. Evidence suggests that corporations cannot hope to beneficially attract investors' attention through advertising without credibly substantiating the positive real cash flows and value effects of advertising outlays.

In view of our results from bond markets, we venture to predict that in instances where visibility enhancement carries material costs for the claimants, the value of increased visibility can be dwarfed by the sheer magnitude of the costs. For instance, in a cross-section of firms, dividend paying firms with a significant commitment to cash disbursement should gain less from advertising than otherwise comparable non-dividend paying firms. Similarly, firms with large bank loans and concentrated private debt may suffer a net loss to their overall value if increased visibility does not lead to real and tangible cash flows improvements. Further research indeed could shed light on the veracity of these predictions.

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Table 1
Variable description and sample statistics

Variable	Description	Mean	Median	Std. Dev.
CSPRD	Credit spread (%)	2.191	1.398	2.265
CRD	Numerical rating	3.843	4.000	1.194
PROPLIQ	Fraction of months in past twelve months with bond trading	0.113	0.000	0.196
LogTVolm	Log of rolling 12 month bond trading volume (‘thousand)	0.829	0.000	1.271
LogEVolm	Log of rolling 12 month equity volume (‘million)	5.720	5.943	1.497
AGE	Number of years past issuance	3.605	2.838	3.197
MAT	Years to maturity	11.408	8.000	10.863
LEVEL	One-year Treasury bill’s yield (%)	3.545	3.450	1.790
SLOPE	Difference between 10-yr. and 2-yr. Treasury bonds’ yields (%)	1.102	0.810	0.932
EUROD	Difference between LIBOR and 3-month Treasury bill yield (%)	0.258	0.200	0.193
SIZE	Log of equity market value plus debt book value	9.733	9.703	1.492
MValue	Equity market value plus debt book value ($B)	16.865	16.366	4.446
LTDB	Long-term debt to total assets	0.370	0.353	0.162
EARNVOL	5-year volatility of EBITDA to assets	0.034	0.022	0.047
ROA	5-year average of net income to assets	0.145	0.146	0.064
QUIK	Cash plus receivables by current liabilities	1.961	0.739	3.179
INTCOV	EBITDA to interest expense	8.945	6.196	10.141
TD2Cap	Total debt to market value of equity	3.085	0.895	7.363
RETVOL	2-year volatility of monthly stock returns (%)	10.029	8.950	5.106
YldVOL	Firm average of rolling 12 month yield volatility	0.011	0.000	0.087
LOGADV0	Log of the current year’s advertising	8.684	8.955	1.642
nLogADV0	Normalized LOGADV0	0.781	0.831	0.230
eA2S5	5-year correlation of sales and lagged advertising	-0.149	-0.226	0.462
neA2S5	Normalized eA2S5	0.192	0.000	0.273

This table reports mean, median and standard deviation of variables in our sample. Our sample consists of 27,792 coupon-paying, plain-vanilla corporate bonds of nonfinancial firms. The corporate bond data are from the Mergent’s FISD database. The sample period covers the years 1994 through 2006. The data for the term structure of interest rates are from the Board of Governors of the Federal Reserve. All accounting data are from annual COMPUSTAT. Stock price and returns are from CRSP.

Table 2
Credit spreads by categories

	Low Sensitivity		High Sensitivity			Small Advertisers		Large Advertisers		
	NOBS	CSPRD	NOBS	CSPRD	Diff.	NOBS	CSPRD	NOBS	CSPRD	Diff.
All Firms	13,955	2.142	13,896	2.241	0.099[a]	13,937	2.848	13,914	1.533	-1.314[a]
Panel A. Credit Rating:										
AAA, AA+, AA, AA-	1,540	0.668	1,434	0.824	0.156[a]	464	0.627	2,510	0.765	0.138[a]
A+, A, A-	4,147	0.957	5,036	1.147	0.190[a]	3,419	1.067	5,764	1.058	-0.008
BBB+, BBB, BBB-	4,256	1.763	4,417	2.093	0.330[a]	4,303	2.004	4,370	1.860	-0.145[a]
BB+, BB, BB-	2,026	3.206	1,822	3.857	0.651	2,861	3.474	987	3.630	0.155[b]
B+, B, B-	1,708	5.022	912	6.099	1.077[a]	2,370	5.400	250	5.374	-0.026
CCC+ and less	278	8.319	275	8.506	0.187	520	8.438	33	8.003	-0.435
Panel B. Maturity:										
Short-term (7 ≤ yrs.)	6,981	2.237	6,281	2.302	0.065	7,304	3.048	5,958	1.311	-1.737[a]
Medium-term (7 < yrs. ≤ 12)	4,015	2.288	3,064	2.262	-0.026	4,133	2.911	2,946	1.386	-1.525[a]
Long-term (yrs. > 12)	2,959	1.719	4,551	2.142	0.423[a]	2,500	2.157	5,010	1.884	-0.272[a]
Panel C. Firm Size:										
Small Firms (Bottom 33%)	4,171	3.588	2,645	3.743	0.155	6,353	3.675	463	3.274	-0.401[a]
Medium Firms (Mid 33%)	4,325	2.009	4,811	2.388	0.380[a]	5,163	2.518	3,973	1.806	-0.712[a]
Large Firms (Top 33%)	5,459	1.142	6,440	1.513	0.371[a]	2,421	1.379	9,478	1.334	-0.045
Panel D. Leverage:										
Low (Bottom 33%)	4,973	1.483	3,820	1.600	0.117[a]	4,613	1.802	4,180	1.238	-0.564[a]
Medium (Mid 33%)	4,666	1.860	5,081	2.099	0.239[a]	4,488	2.486	5,259	1.557	-0.930[a]
High (Top 33%)	4,316	3.205	4,995	2.875	-0.331[a]	4,836	4.181	4,475	1.782	-2.398[a]

This table reports mean credit spreads across credit ratings, maturities, firm sizes, and leverage ratios. Our sample consists of 27,792 coupon-paying, plain-vanilla corporate bonds of nonfinancial firms. The corporate bond data are from the Mergent's FISD database. The sample period covers the years 1994 through 2006. The data for the term structure of interest rates are from the Board of Governors of the Federal Reserve. All accounting data are from annual COMPUSTAT. Stock price and returns are from CRSP. a, b, c denote credit spread differences that are significant at the 1%, 5%, and 10%, respectively.

Table 3
Corporate credit spreads and advertising

	No Fixed Effects	Year Fixed Effects	Year & Industry Fixed Effects	Newey-West Standard Errors	Fama-McBeth Regression	Cross-Sectional Regression
nLOGADV0	**-0.158**	**-0.190**	**-0.124**	**-0.158*****	**7.597**	**-0.050**
	(-1.03)	**(-1.13)**	**(-0.74)**	**(-3.63)**	**(0.96)**	**(-0.31)**
neA2S5	**0.580*****	**0.468*****	**0.424****	**0.580*****	**0.447****	**0.914*****
	(3.37)	**(2.64)**	**(2.53)**	**(13.87)**	**(2.36)**	**(5.64)**
CRD	0.267***	0.292***	0.292***	0.267***	0.183**	0.311***
	(12.05)	(12.44)	(12.71)	(52.86)	(2.29)	(21.97)
LEVEL	-0.186***	-0.409***	-0.411***	-0.186***	2.917	-0.230***
	(-3.55)	(-9.21)	(-9.37)	(-15.29)	(0.87)	(-3.43)
SLOPE	-0.286***	-0.764***	-0.771***	-0.286***	3.353	-0.279*
	(-3.22)	(-9.28)	(-9.49)	(-11.35)	(1.07)	(-1.89)
EUROD	-0.116	0.401***	0.394***	-0.116*	-3.427	-0.820*
	(-0.98)	(5.23)	(5.24)	(-1.77)	(-0.99)	(-1.90)
LogAGE	0.153***	0.151***	0.153***	0.153***	0.106***	0.270***
	(5.35)	(5.18)	(5.83)	(19.90)	(6.89)	(10.15)
LogMAT	0.169***	0.168***	0.156***	0.169***	0.269***	0.066
	(4.20)	(4.16)	(3.66)	(13.66)	(4.37)	(1.47)
RETVOL	0.150***	0.124***	0.127***	0.150***	0.262*	0.133***
	(11.31)	(8.33)	(8.58)	(35.71)	(1.66)	(16.10)
TD2CAP	0.046**	0.047**	0.045**	0.046***	0.076***	0.060***
	(2.23)	(2.21)	(2.23)	(16.92)	(2.86)	(13.13)
LTDB	0.662	0.504	0.397	0.662***	1.521	0.811***
	(1.62)	(1.24)	(0.89)	(6.80)	(1.25)	(3.36)
EARNVOL	1.324*	1.209	1.106	1.324***	-11.588	1.153*
	(1.69)	(1.56)	(1.48)	(6.27)	(-0.88)	(1.84)
ROA	-0.040*	-0.034	-0.050	-0.040***	0.209	-0.053***
	(-1.74)	(-1.43)	(-1.34)	(-10.36)	(0.90)	(-4.54)
QUIK	-2.828**	-2.658**	-2.739**	-2.828***	-0.999	-5.439***
	(-2.12)	(-2.08)	(-2.38)	(-12.15)	(-1.07)	(-8.60)
INTD1	-0.018	-0.025	-0.029	-0.018**	0.175	-0.044
	(-0.47)	(-0.69)	(-0.83)	(-2.10)	(0.92)	(-1.52)
INTD2	0.013	-0.009	-0.013	0.013**	0.916	0.032
	(0.38)	(-0.26)	(-0.36)	(2.13)	(1.01)	(0.84)
INTD3	0.041*	0.034	0.029	0.041***	0.302	0.124***
	(1.73)	(1.21)	(1.07)	(9.35)	(1.00)	(4.39)
INTD4	-0.000	-0.000	0.000	-0.000	-0.018	0.001**
	(-0.23)	(-0.50)	(0.06)	(-0.31)	(-0.95)	(2.40)
Constant	-1.532***	-0.240	0.227	-1.532***	-22.201	-1.054*
	(-3.24)	(-0.55)	(0.46)	(-13.75)	(-1.00)	(-1.93)
N. Obs.	27,792	27,792	27,792	27,792	27,792	1,829
Adj. RSQ	0.6162	0.6355	0.6393	0.6162	0.7203	0.7047

This table reports results of the regression models of credit spread using normalized advertising visibility and sales-advertising sensitivity as test variables. In these regressions, the impact of year, industry, firm, and bond fixed effects are controlled for using a series of dummy variables. The panel regression results with Newey-West *t*-statistics are also reported. The cross-sectional regressions results based on the time-series averages of 27,792 bonds for 1,829 firms are also reported. For brevity, the coefficients on year, industry, firm, and bond dummy variables are not reported. LogAGE and LogMAT are natural logarithms of the bond's age and maturity. INTD1, INTD2, INTD3, and INTD4 are censored interest coverage ratios per Blume et al. (1998). All other variables are defined in Table 1. Robust (heteroskedasticity, autocorrelation, and firm clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Table 4
Impact of advertising on credit spreads across credit ratings and maturities

	AAA – AA Rated	A – BBB Rated	BB – C Rated	Short-term Debt	Mid-term Debt	Long-term Debt
nLOGADV0	0.053	-0.134	0.221	-0.255	0.010	0.039
	(0.94)	(-0.89)	(0.67)	(-1.21)	(0.06)	(0.21)
neA2S5	-0.079	0.295**	1.273***	0.566**	0.725***	0.401**
	(-1.09)	(2.05)	(3.43)	(2.57)	(3.28)	(2.21)
N. Obs.	2,969	17,825	6,998	13,241	7,053	7,498
Adj. RSQ	0.3135	0.3959	0.5333	0.6308	0.6549	0.5822
	Small-Cap Firms	Mid-Cap Firms	Large-Cap Firms	Low Leverage	Medium Leverage	High Leverage
nLOGADV0	0.368	0.027	0.010	-0.152	-0.032	-0.304
	(1.46)	(0.07)	(0.06)	(-0.76)	(-0.14)	(-1.24)
neA2S5	0.610**	0.468**	0.486	0.101	0.758***	1.196***
	(2.08)	(2.19)	(1.64)	(0.56)	(3.03)	(2.65)
N. Obs.	6,794	9,119	11,879	8,777	9,729	9,286
Adj. RSQ	0.5988	0.6530	0.5337	0.4903	0.5491	0.6677

This table reports results of the sub-sample regression models of credit spread using normalized advertising visibility and sales-advertising sensitivity as test variables. A bond is denoted as short-term, mid-term, or long-term if its maturity is, respectively, less than 7 years, between 7 and 12 years, or more than 12 years. A firm is denoted as low-, mid-, or high-leverage if the ratio of its long-term debt to total assets is, respectively, in the bottom, middle, or top tertiles of the COMPUSTAT universe. A firm is denoted as small-, mid-, or large-cap if the sum of its market value equity plus book value of debt is, respectively, in the bottom, middle, or top tertiles of the COMPUSTAT universe. All variables are defined in Table 1. Robust (heteroskadasticity, autocorrelation, and firm clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Table 5
Bond liquidity by categories

	Low Sensitivity		High Sensitivity			Small Advertisers		Large Advertisers		
	LIQ	LogTVolm	LIQ	LogTVolm		LIQ	LogTVolm	LIQ	LogTVolm	
All Firms	0.125	0.914	0.100	0.745	a, a	0.091	0.674	0.135	0.986	a, a
Panel A. Credit Rating:										
AAA, AA+, AA, AA-	0.163	1.127	0.105	0.811	a, a	0.101	0.708	0.141	1.024	b, a
A+, A, A-	0.122	0.890	0.094	0.658	a, a	0.082	0.615	0.121	0.850	a, a
BBB+, BBB, BBB-	0.140	1.026	0.115	0.885	a, a	0.095	0.696	0.159	1.209	a, a
BB+, BB, BB-	0.104	0.782	0.099	0.709	–, a	0.102	0.747	0.103	0.748	–, –
B+, B, B-	0.098	0.746	0.075	0.576	a, a	0.089	0.681	0.099	0.743	–, –
CCC+ and less	0.045	0.367	0.059	0.517	–, a	0.049	0.403	0.091	1.054	a, a
Panel B. Maturity:										
Short-term (7 ≤yrs.)	0.130	0.925	0.102	0.749	a, a	0.091	0.665	0.148	1.058	a, a
Medium-term (7 < yrs. ≤ 12)	0.140	1.077	0.121	0.943	a, a	0.111	0.848	0.161	1.259	a, a
Long-term (yrs. > 12)	0.094	0.666	0.084	0.605	a, a	0.056	0.409	0.104	0.739	a, a
Panel C. Firm Size:										
Small Firms (Bottom 33%)	0.085	0.615	0.067	0.522	b, a	0.079	0.577	0.072	0.601	–, –
Medium Firms (Mid 33%)	0.110	0.810	0.090	0.638	a, a	0.090	0.660	0.111	0.796	a, a
Large Firms (Top 33%)	0.167	1.225	0.122	0.916	a, a	0.124	0.955	0.148	1.084	a, a
Panel D. Leverage:										
Low (Bottom 33%)	0.140	1.012	0.082	0.596	c, b	0.076	0.543	0.158	1.150	a, a
Medium (Mid 33%)	0.133	0.984	0.110	0.827	a, a	0.111	0.834	0.130	0.960	a, a
High (Top 33%)	0.099	0.726	0.105	0.775	a, a	0.087	0.649	0.119	0.863	a, a

This table reports the mean of two measures of bond liquidity (PROPLIQ and LogTVolm) across credit ratings, maturities, firm sizes, and leverage categories. Our sample consists of 27,792 coupon-paying, plain-vanilla corporate bonds of nonfinancial firms. PROPLIQ is the number of trading months in past 12 months. LogTVolm is total number of bonds traded in past 12 months. The corporate bond data are from the Mergent's FISD database. The sample period covers the years 1994 through 2006. The data for the term structure of interest rates are from the Board of Governors of Federal Reserve. All accounting data are from annual COMPUSTAT. Stock price and returns are from CRSP. S&P 500 option data are from OptionMetrics. The overall market volatility index is from the Chicago Board of Option Exchange (CBOE). a, b, c denote credit spread differences that are significant at the 1%, 5%, and 10%, respectively.

Table 6
Corporate bond liquidity and advertising

	No Fixed Effects	Industry Fixed Effects	Industry & Firm Fixed Effects	Newey-West Standard Errors	Fama-McBeth Regression	Cross-Sectional Regression
nLOGADV0	**0.033****	**0.034*****	**0.023****	**0.033*****	**0.018****	**0.051*****
	(2.49)	**(2.96)**	**(2.20)**	**(6.78)**	**(2.06)**	**(5.16)**
neA2S5	**-0.045*****	**-0.038*****	**-0.024****	**-0.045*****	**-0.032*****	**-0.053*****
	(-3.01)	**(-2.70)**	**(-2.36)**	**(-9.78)**	**(-6.81)**	**(-5.24)**
CRD	0.003*	0.004**	0.001	0.003***	0.000	-0.000
	(1.77)	(2.15)	(0.37)	(6.43)	(0.33)	(-0.22)
SIZE	0.017***	0.021***	-0.016*	0.017***	0.020***	0.012***
	(3.21)	(3.91)	(-1.88)	(11.45)	(12.61)	(5.11)
LogEVolm	0.015***	0.014***	0.031***	0.015***	0.003**	0.005***
	(3.84)	(3.86)	(5.74)	(12.41)	(2.25)	(2.69)
YldVOL	0.186***	0.184***	0.163***	0.186***	0.321***	0.210***
	(3.37)	(3.43)	(3.25)	(4.03)	(6.99)	(4.96)
LogAGE	-0.013***	-0.012***	-0.008***	-0.013***	-0.016***	-0.009***
	(-6.39)	(-6.54)	(-3.00)	(-14.53)	(-7.89)	(-5.83)
LogMAT	-0.016***	-0.015***	-0.007*	-0.016***	-0.012***	-0.011***
	(-4.30)	(-4.04)	(-1.70)	(-9.92)	(-7.46)	(-3.75)
Constant	-0.142***	-0.190***	0.088	-0.142***	-0.088***	-0.065***
	(-3.01)	(-3.59)	(1.18)	(-9.89)	(-5.31)	(-2.67)
N. Obs.	27,797	27,797	27,797	27,797	27,797	1,827
Adj. RSQ	0.0646	0.0715	0.1505	0.0646	0.1438	0.1475

This table reports results of the robustness regression models of corporate bond liquidity using normalized advertising visibility and sales-advertising sensitivity as test variables. The proxy for liquidity is PROPLIQ, which is the fraction of trading months in the past 12 months. In these regressions, the impact of year, industry, firm, and bond fixed effects are controlled for using a series of dummy variables. The panel regression results with Newey-West t-statistics are also reported. The cross-sectional regressions results based on the time-series averages of 1,827 bonds are also reported. For brevity, the coefficients on year, industry, firm, and bond dummy variables are not reported. LogAGE and LogMAT are natural logarithms of bond's age and maturity. All other variables are defined in Table 1. Robust (heteroskedasticity, autocorrelation, and firm clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Table 7
Impact of advertising on bond liquidity across credit ratings and maturities

	AAA – AA Rated	A – BBB Rated	BB – C Rated	Short-term Debt	Mid-term Debt	Long-term Debt
nLOGADV0	-0.002	0.019	0.040**	0.036**	0.035**	0.036**
	(-0.09)	(1.01)	(2.51)	(2.07)	(2.02)	(2.44)
neA2S5	-0.051**	-0.037*	-0.029**	-0.033*	-0.039*	-0.061***
	(-2.54)	(-1.76)	(-1.97)	(-1.79)	(-1.75)	(-4.36)
N. Obs.	2,969	17,831	6,997	13,243	7,051	7,503
Adj. RSQ	0.1016	0.0702	0.0681	0.0655	0.0715	0.0787

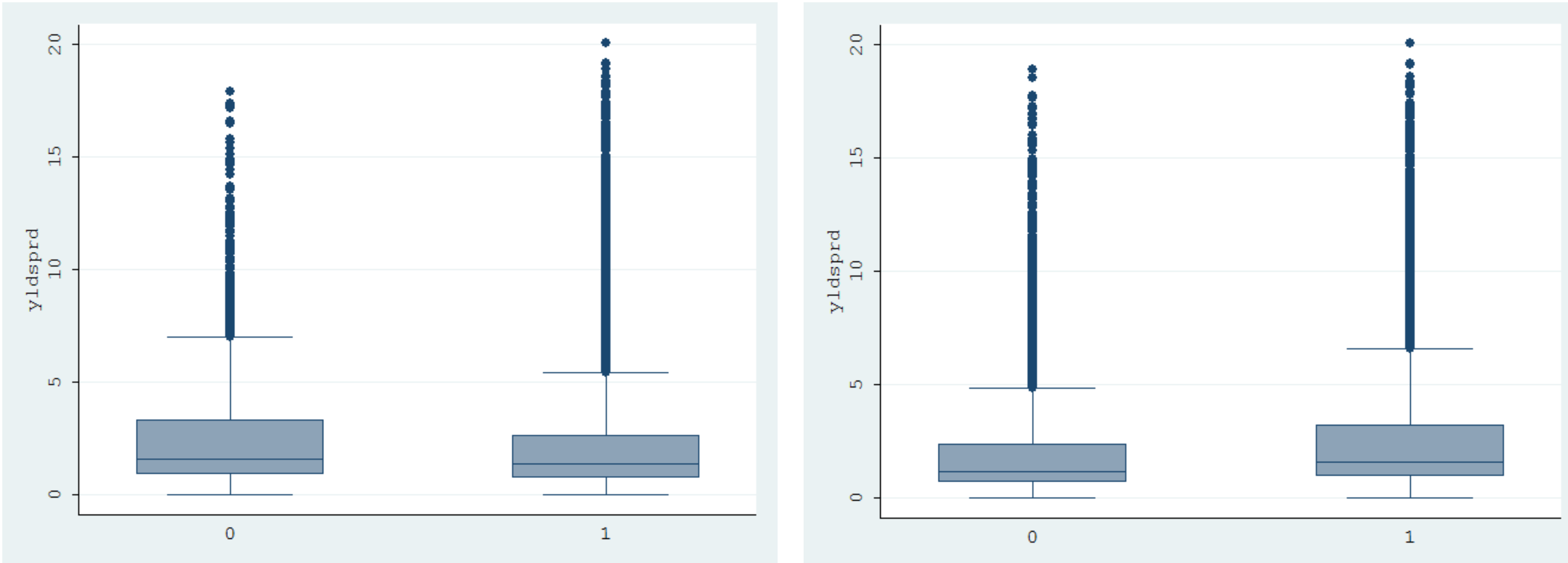
	Small-Cap Firms	Mid-Cap Firms	Large-Cap Firms	Low Leverage	Medium Leverage	High Leverage
nLOGADV0	0.033***	0.027	0.032	0.035*	0.012	0.053***
	(2.61)	(1.05)	(1.18)	(1.79)	(0.56)	(3.26)
neA2S5	-0.028*	-0.014	-0.067***	-0.043**	-0.059**	-0.025
	(-1.78)	(-0.61)	(-2.65)	(-2.34)	(-2.07)	(-1.01)
N. Obs.	6,794	9,121	11,882	8,778	9,732	9,287
Adj. RSQ	0.0503	0.0647	0.0510	0.1014	0.0732	0.0393

This table reports results of the sub-sample regression models of corporate bond liquidity using normalized advertising visibility and sales-advertising sensitivity as test variables. PROPLIQ is the proxy of corporate bond liquidity and is defined as the number of trading months in the past 12 months. A bond is denoted as short-term, mid-term, and long-term, if its maturity is, respectively, less than 7 years, between 7 and 12 years, or more than 12 years. A firm is denoted as low-, mid-, or high-leverage if the ratio of its long-term debt to total assets is, respectively, in the bottom, middle, or top tertiles of the COMPUSTAT universe. A firm is denoted as small-, mid-, or large-cap if the sum of its market value equity plus book value of debt is, respectively, in the bottom, middle, or top tertiles of the COMPUSTAT universe. All variables are defined in Table 1. Robust (heteroskedasticity, autocorrelation, and firm clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

Table 8
Simultaneous equation results for the impact of advertising on credit spreads and liquidity

	Corporate Credit Spread				Corporate Bond Liquidity
PROPLIQ	-2.194***	LTDB	0.734***	CSPRD	0.003**
	(-7.74)		(11.29)		(2.14)
nLOGADV0	0.030	BUSRSK	1.440***	nLOGADV0	0.034***
	(0.65)		(7.64)		(5.74)
neA2S5	0.477***	QUIK	-0.040***	neA2S5	-0.046***
	(13.75)		(-12.79)		(-10.57)
CRD	0.256***	ROA	-3.100***	CRD	0.002**
	(64.57)		(-17.25)		(2.34)
LEVEL	-0.220***	INTD1	-0.019***	SIZE	0.020***
	(-13.81)		(-3.00)		(15.12)
SLOPE	-0.326***	INTD2	0.017**	LogEVolm	0.011***
	(-12.05)		(2.25)		(10.88)
EUROD	-0.159***	INTD3	0.042***	YldVol	0.182***
	(-2.60)		(8.08)		(14.15)
LogAGE	0.124***	INTD4	-0.000	LogAGE	-0.014***
	(16.15)		(-0.03)		(-14.67)
LogMAT	0.141***	Constant	-1.062***	LogMAT	-0.017***
	(11.94)		(-7.27)		(-11.45)
RETVOL	0.154***			Constant	-0.143***
	(69.96)				(-10.16)
TD2CAP	0.046***	N. Obs.	27788	N. Obs.	27788
	(35.44)	Adj. RSQ.	0.5986	Adj. RSQ.	0.0619

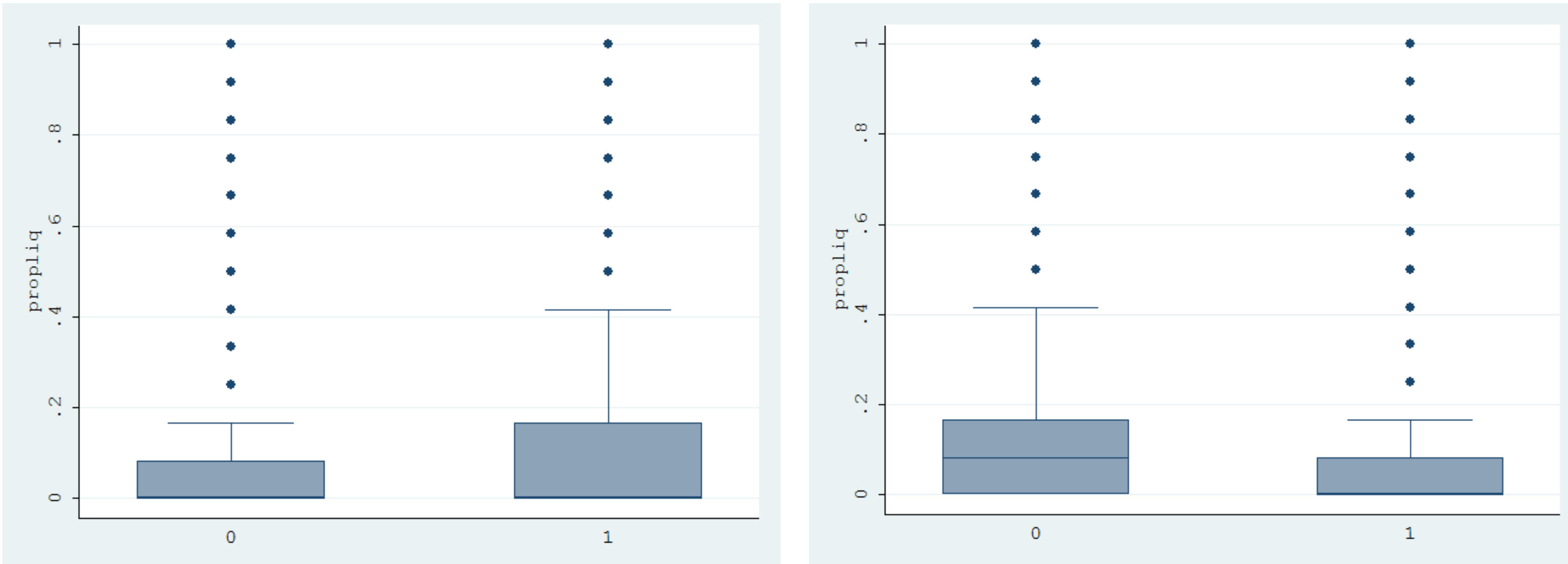
This table reports the results of a simultaneous system of equations estimation for credit spreads and liquidity using normalized advertising visibility and sales-advertising sensitivity as test variables. LIQ is the proxy of corporate bond liquidity and is defined as the number of trading months in the past 12 months. LogAGE and LogMAT are natural logarithms of bond's age and maturity. INTD1, INTD2, INTD3, and INTD4 are censored interest coverage ratios per Blume et al. (1998). All other variables are defined in Table 1. Robust (heteroskedasticity, autocorrelation, and firm clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.



Panel A Panel B

Figure 1. Credit spreads and advertising visibility and sales-advertising sensitivity

Panel A plots credit spreads and advertising visibility (above and below median of nLOGADV0). Smaller advertisers are denoted by zero. Panel B plots credit spreads and sales-advertising sensitivity (above and below median of neA2S5). Low sales-advertising sensitivity is denoted by zero. The 25^{th} – 75^{th} percentiles are limits of the gray box with the median shown by a line in the middle. The next biggest and smallest observations are shown using bars. The outliers are shown with diamonds.



Panel A

Panel B

Figure 2. Bond liquidity and advertising visibility and sales-advertising sensitivity

Panel A plots bond liquidity and advertising visibility (above and below median of nLOGADV0). Smaller advertisers are denoted by zero. Panel B plots bond liquidity and sales-advertising sensitivity (above and below median of neA2S5). Low sales-advertising sensitivity is denoted by zero. The 25^{th} – 75^{th} percentiles are limits of the gray box with the median shown by a line in the middle. The next biggest and smallest observations are shown using bars. The outliers are shown with diamonds.