Short Interest and Credit Spreads

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Abstract

There has been considerable debate on whether short sales have pertinent information about firm fundamentals. We examine whether short interest is informative about corporate bond prices. We find empirical evidence that short interest is a negative signal about a firm's debt securities. Highly shorted firms have higher credit spreads and experience increase in credit spreads in the subsequent months. These findings indicate that bond investors use the information contained in short interest to price bonds. Therefore, our results that identify an informational relationship between short interest and bond prices provide an independent verification of the extant evidence on stock prices regarding short sellers' role as detectives of firm value.

JEL classification: G10, G11, G12

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I. Introduction

The purpose of this article is to examine the relationship between short selling in the equity market and bond prices. Several studies demonstrate that bond prices (credit spreads) are correlated with earnings and cashflows (Callen et al. (2009), among others). If short sellers are informed about firms' fundamental values in terms of future earnings or cash flows, the level of short selling could be informative regarding credit spreads. To the extent that short selling in the equity market signals bad news about a firm's performance, the level of short interest could be related to its credit yields. In this paper, we contribute to the literature by investigating the importance of short selling activity in the equity market in explaining the cross-sectional variation in credit spreads on corporate debt after relevant variables for bond pricing such as issue and firm characteristics are controlled for.

Our study is the first to provide empirical evidence on the relationship between short interest and bond prices. We examine whether short interest is informative about corporate bond prices or credit spreads and find consistent evidence. Firms with higher short interest tend to have higher credit spreads than otherwise similar firms. Moreover, firms with higher short interest experience increases in credit spreads over the subsequent months. Specifically, there is about 40 basis points difference in credit spreads (depending on specifications) between top ten percent and bottom ten percent of firms based on short interest. Moreover, firms that experience increase in short selling activity also experience increase in their credit spreads. We find that for every one percent difference of short interest increase, credit spreads increase by 2-3 basis points, depending on model specification, among otherwise identical bonds. These findings indicate that the information contained in short interest is priced in the bond market.

We use bond securities of industrial firms that have no option like features that span the years 1994 through 2006. We begin our empirical analysis by providing general characteristics of firms, which short sellers target. We find that short sellers generally target bonds with lower credit ratings, firms with lower profitability, higher leverage, and higher volatility. Since these variables are also determinants of credit spreads, we control for them in our analysis throughout this paper. We estimate predictive panel regressions of credit spreads on short interest controlling for a host of firm and issue characteristics such as credit rating, financial leverage, profitability, equity return volatility, bond liquidity and time to maturity, and macroeconomic variables. In all of the specifications, short interest is positively and significantly related to credit spreads. Highly shorted firms seem to have higher credit spreads than otherwise similar firms. Furthermore, when we group our sample in terms of firm characteristics, we find that this effect is more pronounced for bonds with lower credit ratings and highly levered firms. We also confirm the robustness of our results in clustered panel regressions as well as Fama-MacBeth cross-sectional regressions. In sum, we conclude that our results are consistent with the notion that short interest is informative about firm fundamentals and therefore its bond prices.

Although there is a large body of work examining short selling and equity price relationships, this paper is the first to study short selling and bond prices. Our results are consistent with the extant literature on short selling that conjecture short sellers as sophisticated investors and document that short interest or shorting flow correctly predict negative future abnormal stock returns. Diether et al. (2009), Boehmer et al. (2009) find that short selling flow predicts future negative abnormal returns. Dechow et al. (2001), Asquith et al. (2005), among others, provide evidence of a negative relationship between short interest and subsequent stock returns. Short sales may predict subsequent stock returns because short sellers are capable of detecting stock price deviations from fundamental values and trade when equity values are temporarily overpriced; thus moving prices toward fundamental value. If short sellers' information is only based on temporary overpricing caused by short selling constraints (as argued by (Miller 1977)) or other market frictions in the equity market, these studies cannot conclude if short sellers possess any fundamental information about the firms they trade. Using bond prices enables us to address this issue since bond prices should be free of any pricing frictions in the equity market. The significant relationship between short interest and bond prices documented in this study demonstrates that short seller's information advantage is not only about discovering temporary overpricing in the equity market but also about uncovering fundamental value of the firms they trade. This is one of the important contributions of this article.

There are some earlier papers that advocate that short sellers may also be informed about future fundamental values, and therefore, the negative relationship between short interest and subsequent stock returns may be driven, in part, due to short sellers' informativeness regarding fundamental values such as earnings. Consistent with this idea, those studies find that short sellers target firms with poor earnings quality (Desait et al. (2006)) and high accruals (Hirshleifer et al. (2009)), firms that experience negative earnings surprises (Christophe et al. (2004)), downward analyst forecast revisions and negative earnings surprises (Akbas et al. (2009)). Our paper is closest to these papers that investigate the relationship between short selling and some form of fundamental value and find that short interest provides value-relevant information about future changes in fundamental value. If short sellers have superior ability to detect deteriorating fundamentals and bond prices are not directly affected by institutional frictions in the equity market like short selling constraints, information contained in short interest may predict future bond prices as we document in this paper since bond prices are a function of future fundamental values. Our approach of using bond prices has one advantage over the preceding work since we use transaction prices observed in the bond market rather than accounting variables to detect the informativeness of short selling about future fundamentals.

Our paper is also related to papers that study the association between credit spreads and firm characteristics, which have known effects on equity values. A firm attribute may have differing impacts on its equity and bond values or expected returns. For instance, although Gompers et al. (2003) show that antitakeover governance provisions are negatively related with equity values, Klock et al. (2005) find that the same antitakeover provisions are associated with higher bond values (or lower credit spreads). Similarly, Diether et al. (2002) demonstrate that stocks with high analyst forecast dispersion earn lower future returns. They interpret their results being consistent with the argument that in the presence of short selling constraints, stocks with greater divergence of opinions would be overpriced. However, in the bond market, Guntay and Hackbarth (2009) find that bonds of firms with higher dispersion have higher credit spreads and future bond returns. They argue that the effect of forecast dispersion on stock returns differs from the one on bond returns since short selling constraints in the bond markets are not as significant as they are in the equity markets. In a similar manner, if the association between short interest and subsequent stock returns is merely based on equity market conditions or mis-valuations, then there would not be a relationship between short interest and future bond prices. The fact that we see a similar relationship in the bond market suggests that short interest and return relationship is, in part, based on fundamental information. Therefore, the results in our paper demonstrate that short sellers have fundamental information regarding the firms they are targeting.

II. Literature Review

There is a broadening base of empirical research demonstrating that short sellers are informed investors. Diamond and Verrecchia (1987) point out that short sellers do not have access to their proceeds due to collateral requirements. This precludes short selling for liquidity reasons, and therefore, leads to the idea that a short seller is relatively more informed than an average investor. Therefore, short seller has a net informational advantage (acquisition or processing) over other investors. If informed investors are more likely to engage in short selling, high short interest conveys adverse information. Do short sellers have inside information? We would like to think of them as sophisticated investors with superior analytical skills in terms of processing information contained in financial statements or various news sources. James Chanos from Kynokos Associates, a fund that specializes in short selling, supports this idea and states that "short sellers conduct a rigorous financial analysis and find fundamentally overvalued securities that are poised to fall in price".

The extant literature on short selling documents that short sellers are successful in identifying stocks that subsequently underperform the market. Desait et al. (2002) find that heavily shorted firms experience significant negative risk adjusted returns and suggest that high levels of short interest is a bearish signal. Cohen et al. (2007) contend that shorting demand signals informed trading. By differentiating between supply and demand shifts in the shorting market, they show that stock returns are only predicted by changes in shorting demand, not shorting supply. Boehmer et al. (2009) examine daily shorting flows and show that short sellers can identify overvalued stocks and that highly shorted stocks earn significantly lower abnormal returns than lightly shorted stocks. They document that institutional nonprogram short sales are the most informative. In a similar study that examines shorting flow, Diether et al. (2009) find that short sellers increase their positions after price increases and predict future negative abnormal returns. They conclude that short sellers are successful in detecting short term deviations of stock prices from fundamental value due to market frictions and by targeting overpriced stocks profit from their trades. Dechow et al. (2001) document that short sellers target firms that priced high relative to earnings or book value and unwind their positions as these ratios mean-revert, thereby earn above normal returns. They advocate that short sellers take positions in stocks they believe to be temporarily overpriced. In sum, these studies suggest that short sellers are highly informed traders targeting temporarily overpriced stocks.

However, Asquith et al. (2005) argue that stocks with high short interest are short selling constrained and that the ability of short interest to predict subsequent returns is due to such market frictions. They argue that restrictions in the market for borrowing shares may cause a stock to be overvalued and generate low subsequent returns. The greater the shorting costs, the greater the possible overpricing; and therefore, the lower the subsequent stock returns. Consistent with that assertion, they find that stocks with high levels of short interest (shorting demand) and low institutional ownership (shorting supply) subsequently earn lower abnormal returns. Similarly Jones and Lamont (2002) find underperformance among stocks with high shorting costs in the 1930s.

On the other hand, Akbas et al. (2009) demonstrate that low future returns of highly shorted stock is due to short sellers' ability to predict future firm performance. They show that short sellers are informed investors who predict negative stock returns by correctly anticipating negative earnings surprises, unfavorable public news, and downward analyst forecast revisions. Therefore, they posit that short sellers are informed investors who take positions in stocks that are about to experience decline in fundamental values. Moreover, they also document that short interest in stocks with low institutional ownership is the most informative of future fundamentals. Finally they show that return predictability is closely correlated with short sellers' ability to anticipate future changes in fundamentals. There are also some recent studies that explore the relationship between short selling and non-price related firm performance to find out whether short sellers have value relevant information. For example, Christophe et al. (2004) show that negative earnings surprises are preceded by unusually high short selling activity, which indicates informed trading. Desai et al. (2006) find that short sellers are able to identify and take position in firms that announce earnings restatements and subsequently unwind their positions after the announcement. The authors assert that the purpose for short selling is, at least in part, related to earnings quality or questionable accounting practices. In a similar work, Karpoff and Lou (2009) demonstrate that short sellers anticipate the discovery and severity of financial misconduct. They find that short interest increases in the months before the financial misrepresentation is disclosed to the public. Hirshleifer et al. (2009) find a positive relationship between short interest and accruals. Since firm fundamentals such as earnings are the main driving factors of equity values as well as bond values, if short sellers have superior ability to detect deteriorating fundamentals, then we could observe a significant relationship between short interest and credit spreads. This is the purpose of our study.

III. Empirical Methodology

Following the trains of thoughts from our literature review, we conduct empirical tests to address one main question: Does high short selling activity lead to larger credit spreads? The initial basic regression model used in the paper is a panel regression OLS model as follows:

$$CSPRD_{i,t} = \alpha + \beta_1 \, SHORT_{i,t-1} + \mathbf{\Phi} \, \mathbf{X}_{i,t} + \varepsilon_{i,t} \tag{1}$$

where the dependent variable ($CSPRD_{i,t}$) is the credit spread on the debt issue of firm *i* at time *t*;

$SHORT_{i,t-1}$ is the proxy for the short interest of firm i at time $t-1$, and $\mathbf{X}_{i,t}$ is a vector of control variables for firm i at time t. The explanatory variables in $\mathbf{X}_{i,t}$ attempt to control for macroeconomic conditions, bond-level characteristics, and firm-level attributes. The following sections discuss these control variables at length. To prevent estimation biases in the time-series, we also include time-series fixed effects in the regressions. There are industry-level, firm-level, and bond-level dummies in the baseline model to ensure that the results regarding the relationship between short selling activity in the equity market and credit spreads is not largely due to spurious cross-sectional correlations between credit spreads and other bond and firm characteristics.

A. Dependent Variable: Credit Spread

Empirically, the credit spread is often computed as the difference between the corporate bond yield and the fitted yield on an otherwise equivalent Treasury bond. Following Duffee (1998) and Collin-Dufresne, Goldstein, and Martin (2001), we use a linear interpolation scheme for the month-end Treasury yield rates reported by the Federal Reserve Board of Governors (Fed) for maturities 1, 2, 3, 5, 7, 10, 20, and 30 years to approximate the entire yield curve. Since only yields on the aforementioned bonds are available from the Fed, we use interpolation to find what the corresponding Treasury yield would be for each of the corporate bonds in the sample. 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.[1]

B. Test variable: Short Selling Activity

To measure the degree of short sales, we use the level of short interest calculated as the number of shares shorted reported by the exchanges (NYSE, NASDAQ, and AMEX) divided by the total number of shares outstanding of a particular firm. Since we investigate whether short sellers have value relevant information about a particular firm, we examine the behavior of bond prices either contemporaneously or after short selling activity is observed. Therefore, short interest variable is measured the same month or one month before the credit spread variable is measured. Moreover, in addition to using the actual level of short interest, we also measure standardized values as follows. Each month, we transform the short interest variable into decile ranks and standardize them to take values between zero and one. This transformation makes the coefficient interpretation more intuitive and minimizes the effect of outlier observations. In this setting, the coefficient estimate would measure the credit spread difference between firms with short interest in the highest and lowest decile. We use two measures of standardized short interest. SI1R is based on all firms with short interest data without regard to the availability of corporate bond data. SI2R is measured similar to SI1R but only using firms, which we have available data on corporate bonds.

C. Control Variables

We include a large number of standard control variables to ensure that known determinants of credit spreads do not confound the impact of the test variables. Since we would like to find out whether short sellers convey negative information about future bond prices above and beyond factors commonly known, the following control variables are used. The choice of credit spread determinants is largely based on Elton et al. (2001), Collin-Dufresne, Goldstein, and Martin (2001), Campbell and Taksler (2003), Chen, Lesmond, and Wei (2007), and Guntay and Hackbarth (2007). Theoretically, firms with a higher default probability and/or lower expected recovery rates have higher credit spreads. Thus, various macroeconomic, bond-specific, and firm-specific proxies can control for common default and recovery risk factors. Table I provides a list of all variables with brief descriptions. The main control variables are defined as follows:

1. *Credit rating*. As in Collin-Dufresne, Goldstein, and Martin (2001) and Chen, Lesmond, and Wei (2007), we use this numerical rating, CRD, as a determinant of credit spreads. We follow the convention of COMPUSTAT to assign numerical values for different ratings. So, for instance, a value 2 denotes AAA rating whereas a value 4 denotes A rating. We use the average of Moody's rating and Standard and Poor's rating unless one is not available, in which case is the available rating is used.
2. *Risk-free rate*. In structural models of credit risk, a rise in the spot rate effectively reduces the likelihood of default (Leland 1994 and Longstaff and Schwartz 1995). Previous empirical studies (Duffee 1998 and Chen, Lesmond, and Wei, 2007) indicate that credit spreads tend to fall when Treasury yields rise. As such, we use the 1-year Treasury bill yield, LEVEL, as a determinant of credit spreads.
3. *Treasury term structure*. The slope of the term structure of the Treasury interest rates seems to have explanatory power in predicting both interest rate movements and macroeconomic growth (Litterman and Scheinkman 1991). In a structural model, Ju and Ou-Yang (2006) show that as the yield curve becomes steeper, the credit spreads widens. We thus use the difference between Treasury 10-year and 2-year constant maturity bonds' yields, SLOPE, as a determinant of credit spreads.
4. *Treasury Liquidity*. As in Chen, Lesmond, and Wei (2007), we use the spread between 3-month Euro-dollar rate and the 3-month Treasury bill yield, EURO, to capture the Treasury bonds' "crowding out" adverse liquidity effect.

5. *Years-to-Maturity*. Merton (1974) shows that credit spreads and maturity are nonlinearly related and this relationship is a function of credit quality. Helwege and Turner (1999), however, find that, on average, the term structure of credit spreads is upward-sloping. The log maturity of a bond, LogMAT, is included to describe the shape of the credit spread term structure.
6. *Age*. Bond age has been shown to relate positively to credit spreads (see Warga 1992, Perraudin and Taylor 2004, and Yu 2005). We include the log of bond age, LogAGE, and define it as the log of the difference (in years) between the settlement date and the issuing date.
7. *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). Since firm value and its volatility are unobservable, as suggested by Campbell and Taksler (2003), we choose equity volatility, RETVOL, instead. Specifically, we define RETVOL as the annualized standard deviation of the firm's monthly stock returns over the preceding 24 months.
8. *Liquidity*. Recent work indicates that liquidity is a priced risk in corporate bonds' credit spreads (Chen, Lesmond, and Wei 2007 and Covitz and Downing 2007). We use Guntay and Hackbarth's (2007) measure of liquidity as a bond-level proxy for liquidity. We count the number of months a bond has a market quote during the past 12 months. We define liquidity, LIQ, as this count divided by 12 to standardize this measure to the unit interval.

The following variables further control for credit spread risk factors:

9. *Total debt to capital*. Default risk, or the ability to meet pay outstanding debt, is directly related to amount of debt outstanding. In fact, the ratio of debt to value plays a pivotal role in

structural models. As in Chen, Lesmond, and Wei (2007), we use the ratio of the book value of total liabilities to market value of equity, TD2Cap.

10. *Earning volatility*. As noted previously, the unobservable asset volatility matters greatly for credit spreads. Campbell and Shiller (1988a, 1988b) and Campbell (1991) show that expected equity return represents shocks to the dividend stream as well as shocks to discount rates. We choose historical earnings volatility, VOLEARN, to capture expected riskiness of the future earnings stream. Specifically, we use the 5-year standard deviation of ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to assets.
11. *Profitability*. Firms with a higher operational income can meet their debt service easier and hence are less likely to default in the near future. As in Guntay and Hackbarth (2007), we use the ratio of earnings before tax and depreciation divided by book value of total assets.
12. *Quick ratio*. In short term, the inability to meet debt obligations can be mitigated by liquid assets. We use the quick ratio (i.e., the ratio of cash and receivables to total assets) as a measure of asset liquidity.
13. *Interest coverage*. The ability to meet periodic debt service is the first test in determining whether a borrower is at default. Following Chen, Lesmond, and Wei (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).

IV. Data and Summary Statistics

A. Data

We start with all bonds issued by US firms that can be identified in the Fixed Income Database (FISD), as provided by Wharton Research Data Services (WRDS), for the period of 1994 to 2006 to construct a sample of potential corporate bonds. Our main focus is on bond transactions as reported by FISD.[2] As is the convention of previous papers, the payout characteristics of bonds in this sample are similar; hence we exclude all bonds with option-like features such as callability, putability, convertibility, and sinking fund provisions convertibility. Additionally, we exclude zero-coupon and floating-rate bonds. We also delete the bonds without ratings by either Standard & Poors (S&P) or Moody's. Similar to previous bond pricing studies (see e.g. Collin-Dufresne, Goldstein, and Martin 2001 and Eom, Helwege, and Huang 2004), we exclude regulated industries (i.e. financial services and utilities). This leaves us with 1,560,430 potential transactions.

Following extant literature (Collin-Dufresne, Goldstein, and Martin 2001, Yu 2005, Chen, Lesmond, and Wei 2007, and Guntay and Hackbarth 2007), we use a number of independent variables as typical control determinants of credit spreads like macroeconomic factors (i.e., Treasury term structure and Euro-dollar rate), stock-related attributes (i.e., stock return volatility and total liability to capital), accounting characteristics (i.e., leverage, liquidity, business risk and profitability). The filtered data is then merged 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, which leaves us with 407,778 firm-month transactional observations, and then merge the data with data from monthly CRSP. We use monthly CRSP to obtain stock prices, stock return volatility, and market volatility. We only keep firms that have valid transaction month-end's stock price and rolling two-year return standard deviation. The resulting sample contains 403,150 firm-month observations. We use the COMPUSTAT annual database to obtain accounting information about the firms such as leverage, interest coverage, quick ratio, profitability, earnings volatility, and earnings management (accruals). We require firms to have valid accounting measures in the year prior to the transaction. Some of accounting characteristics are, however, multi-year averages. In general, for a firm to be considered, accounting information must be available for three years prior to the transactions. To avoid biases due to outliers, all of the accounting characteristics are winsorized at the 2% level (i.e. observations are trimmed at the 1% level at both tails). After merging the transaction data with COMPUSTAT and short interest data, the final sample includes 62,935 firm-month observations. These firm-month observations come from 1174 firms with 90% of them having less than 183 observations.

B. Summary Statistics

Table I provides summary descriptive statistics for the variables employed in the analysis. In Table 1, the mean credit spread for the sample of new bond issues is 2.147 percent. The mean 2-year T-bill yield at the time of issue is 3.508 percent and the mean difference between 10- and 2-year T-bond yields at the time of issue for the sample is 1.126 percent. Duffee (1998) shows that on average credit spreads are between 0.67 to 1.42 percent 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 percent over the period of 1987 to 1996. They also find that the corresponding Treasury yields range from 5.265 to 8.382 percent.

The sample characteristics used here are somewhat comparable with previous studies, considering that this paper's sample spans the period of 2000 – 2004 when credit spreads and Treasury yields were, respectively, at historically high and low levels. Firms in our sample have a mean size of about $12.5 billion and generate a net positive return on assets (EBITDA is 13.5 percent of assets, on average). The mean long-term debt ratio for the sample firms is about 36 percent, which is comparable to those reported in other related studies such as Collin-Dufresne, Goldstein, and Martin (2001). Overall, firms in the sample are large, profitable firms with relatively low leverage. For our sample of bonds, the mean years-to-maturity is 11.293, which is comparable to the samples in previous empirical studies (see Collin-Dufresne, Goldstein, and Martin 2001, Graham 2000, and Guntay and Hackbarth 2007). The mean short interest in our sample is 2.677 percent, which is comparable to the previous studies such as Asquith et al. (2005). We also note that average short interest in the market is in an increasing trend from the beginning of our sample getting as high as 4 percent through the end.

[Insert Table I here.]

C. Univariate analyses and sample comparisons

To gain insight into the relation between short interest and expected credit spreads, we examine their univariate relation in the cross-section and over time. Figure 1 plots the credit spread of each bond versus short interest and shows that there is a positive relationship between short interest and credit spreads: highly short-sold firms, have larger credit spreads. In fact, when the distribution of credit spreads is plotted across short interest tertiles, the positive association between short interest and credit spreads rises exponentially with short interest.

Table II provides a comparison of credit spreads across industries, ratings, maturities, firm sizes, and leverage levels. Credit spread is higher for highly shorted firms when industry and certain bond characteristics are held constant. The majority of bonds in the sample are in consumer goods, auto, and retail industries. However, the credit spreads are largest for highly shorted firms in certain subsamples. Highly short sold firms suffer most in auto, machinery, and metals industries. For example, in consumer goods industry, highly shorted firms' average credit spread is 2.510 percent while lightly shorted firms have average 1.478 percent credit spread. When we look at the results across credit ratings, we see that the credit spread difference between firms with high and low short interest is considerably lower, albeit still positive.

Among firms with BBB and BB ratings, the highly short-sold firms face, respectively, 39 and 37 basis points of larger credit spreads. The highly short-sold firms' short-term bonds have a 135-basis-point larger spread while their long-term bonds have a 92-basis-point larger spread. The highly short-sold firms' with high leverage have a 152-basis-point larger spread while those with low leverage have a 65-basis-point larger spread. The impact of the firm size on the impact of short selling on credit spreads is nonlinear. The highly short-sold mid-sized firms face a 116-basis-point larger spread.

[Insert Table II here.]

Our sample comparisons confirm the basic idea that higher short interest lead to larger credit spreads. The unconditional credit spread difference between high and low short interest firms is 1.210 percent and highly statistically significant as reported in Table III. However, short sellers might be targeting firms with specific characteristics that predict high credit spreads. For instance, short sellers could target firms with lower credit ratings, higher earnings or return volatility. To understand to what extent short interest relate to other firms attributes, we perform a sample comparison across firms with different short interest levels. As presented in Table III, almost all firm attributes of interest are related to short interest. It is worth noting that higher short interest also corresponds to greater credit risk. For instance, while high short interest firms have an average credit rating of 4.384, a low short interest firm has a 3.462 rating. Similarly, high short interest firms are less profitable, more levered, and have greater volatility than their low short interest counterparts. The highly short-sold firms have 38% long-term leverage, 11.7% stock return volatility, and 12.3% profitability whereas low short-sold firms have 33% long-term leverage, 8.9% stock return volatility, and 14.8% profitability. Such regularities raise the pertinence of controlling for correlations among different determinants of credit spreads in a multivariate setting. Therefore, in the next section we perform multivariate analyses of credit spreads and try to find out if short interest has any predictive ability for credit spreads after controlling for relevant credit spread factors.

[Insert Table III here.]

V. Empirical Results

As discussed previously, we estimate a reduced-form empirical model of credit spreads which in essence is a linear regression of credit spreads on short interest and common control variables. We first begin to run a series of pooled ordinary least squares (OLS) regressions, with different fixed effects, to illustrate the relation between credit spreads and short interest, while also controlling for various fundamentals, such as interest rates, bond-level liquidity, leverage, firm size, and book-to-market. In particular, we explore how short interest effect is distinct from other common measures of credit risk, such as credit rating and maturity. To examine the nonlinearity of the impact of variables such as ratings, maturity, firm size, and leverage, we then stratify the panel into subsets of firms and re-estimate the baseline model. This demonstrates that the paper's main findings are largely confirmed within various subsamples of the panel. In an effort to explore the robustness of the results compared to alternative econometric specifications, we then use the full sample and estimate the baseline model under different specifications with Newey-West standard errors and Fama-MacBeth regressions. Lastly, to explore the pertinence of intertemporal short interest, we estimate the first model over time and further estimate a linear regression model of the monthly changes of credit spreads as a function of short interest and monthly changes in short interest.

As noted, the paper's main hypothesis is that if short sellers have any ability to detect deteriorating fundamentals, higher short selling activity (i.e., short interest) should predict higher credit spreads. To directly address this issue, we estimate the empirical model as represented by Eq. (1). Consistent with our main hypothesis, we find that credit spreads do increase with short interest, as displayed in Table IV. The regression coefficients corresponding to one-month lagged short interest as well as overall and in-sample short interest rankings are positive and statistically significant at better than 5 percent. All the regressions use robust (i.e. White's 1980 heteroskedasticity adjusted), with standard errors corrected for correlation across multiple observations of a given firm (i.e. firm-level clustering). All models have reasonably high explanatory power as indicated by R^2s that exceed 75 percent and are comparable to recent research on credit spreads (see, e.g., Guntay and Hackbarth 2007 and Klock, Mansi, and Maxwell 2004).

The coefficient on one-month lagged short interest, depending on specifications, is 0.048 or 0.055 (statistically significant at the 1% level). The estimated coefficient on short interest suggests that for every percentage rise in short interest, the bond credit spread rises approximately by 5 basis points. The coefficient on short interest ranking based on all firms with available short interest data, depending on specifications, is 0.298 or 0.519 (statistically significant at the 1% level). Similarly, the coefficient on in-sample short interest ranking, depending on specifications, is 0.161 or 0.284 (statistically significant at the 1% level). The estimated coefficient on in-sample short interest raking suggests that the bond credit spread is at least 16 basis points higher for highly short firms compared to lightly short firms when other relevant variables for credit spreads are controlled for. These findings support the paper's prediction that credit spreads are an increasing function of short interest.

[Insert Table IV here.]

All of the control variables, regardless of model specification, exhibit signs in the predicted direction. For example, 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. The proxy for equity risk, per se RETVOL, exhibits the predicted positive sign. More profitable (as measured by ROA) 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. Lastly, longer maturity (LogMAT) and older bonds (LogAGE), also exhibit expected positive signs. Bonds with more trading liquidity (LIQ) have smaller spreads.

VI. Robustness Analyses

A. Short Sale Effects across Ratings, Maturities, Firm Size, and Leverage

A main concern for this analysis is whether the effect of the short selling is confounded by the inherent nonlinearity of the term structure of credit spreads. Extant structural models suggest that the term structure of credit spreads is nonlinearly related to the firm's credit quality, debt maturity, and perhaps firm size and leverage levels. Merton (1974) shows that the shape of the credit spread curve changes as the firm's leverage and earnings' volatility change. Duffee (1998) and Yu (2005) find that credit spreads and other measures like bond maturity and firm size are also linked in a pronouncedly nonlinear fashion. To control for these nonlinearities, we follow the convention of extant literature (e.g., Collin-Dufresne, Goldstein, and Martin 2001, Campbell and Taksler 2003, Chen, Lesmond, and Wei 2007, Yu 2005, and Guntay and Hackbarth 2007) and estimate the baseline regression model separately for firms sorted on credit rating, bond maturity, firm size, and leverage. Using these attributes (i.e., rating, maturity, size, and leverage), we divide the sample into tertiles and run baseline regressions for sub-samples.

The results are reported in Table V and suggest that the negative relation between short interest and credit spread is robust. However, important nonlinearities exist in regard to how short interest affect credit spreads. The coefficient estimates of short interest are only statistically significantly positive for low rating firms. The coefficient estimates for the contemporaneous are 0.039 and 0.034 for mid-, and low-rated bonds, respectively (statistically significant at better than the 1 percent level). The coefficient estimates for the all-firm short interest ranking are 0.465 and 0.510 for mid-, and low-rated bonds, respectively (statistically significant at better than the 1 percent level). The impact of short interest in the credit spread is increasing with firm size. The coefficient estimates for the contemporaneous short interest are only statistically significant for midsized and large firms and equal to 0.030 and 0.135, respectively. The coefficient estimates for the all-firms short interest ranking are statistically significant for midsized and large firms and equal to 0.821 and 0.691, respectively.

Table V shows that the impact of short interest in the credit spread in nonlinear with maturity. The coefficient estimates for the contemporaneous short interest are only statistically significant for short- and long-term bonds and equal to 0.073 and 0.073, respectively. The coefficient estimates for the all-firms short interest ranking are statistically significant for short-, mid- and long-term bonds and equal to 0.462, 0.303 and 0.549, respectively. Based only on the coefficient estimates for contemporaneous short interest, the short selling's impact on credit spreads are also nonlinear. The coefficient estimates are only statistically significant for low and high leverage firms and equal to 0.033 and 0.076, respectively.

These results confirm our main hypothesis that the positive impact of short selling on credit spreads is due to the Diamond and Verrecchia (1987) information channel theory. If increase in short selling signals deterioration of firm fundamentals, we expect to see the positive association between short selling and credit spreads to get magnified with credit rating and leverage.

[Insert Table V here.]

B. Alternative Model Estimation

One concern in estimating a baseline model is the impact of time-series correlation on residuals. We address this concern in three different ways: Newey-West, Fama-MacBeth and pure cross-sectional estimations. Our Newey-West standard errors estimates for the main test variable and almost all other regressors remain intact. The coefficient estimates for contemporaneous and lagged short interest are similar to the ones in the baseline model. We also implement the Fama-Macbeth approach by running cross-sectional regressions for each month and reporting the average coefficient estimates. We find that the short interest is significant at the 1 percent level. Lastly, to further verify the results, we run a pure cross-sectional regression based on the time-series averages of bond-level observations. Under this alternative econometric specification, both the economic and statistical importance of the short interest remains similar to the Newey-West and Fama-McBeth results.

[Insert Table VI here.]

C. Credit Spread Changes and Short Interest

To further assess the pertinence of short interest for the credit spread, we examine how monthly changes in short interest affect changes in the credit spreads. In a large panel data, most of the identification comes from the cross-sectional information. The cross-sectional relation could then lead to noisy estimations because short interest could proxy for the firms' credit risk. Incorporating firm fixed effects and various firm-level credit risk factors can address this concern, but we learn more about our fundamental hypothesis by additionally studying the relation between the changes in credit spreads and the changes in short interest. Of course, as noted by Collin-Dufresne, Goldstein, and Martin (2001), this represents an opportunity to study an important subject of interest: finding determinants of changes in credit spreads. More importantly, such an analysis can also show how short selling affects bond portfolio returns.

By defining changes in credit spreads, $\Delta CSPRD_{i,t}$, as the difference in credit spreads between two months, $\Delta CSPRD_{i,t}$. we arrive at a total of 55893 observations in the full sample from January 1994 to December 2006. To test the paper's main prediction that higher short interest leads to larger credit spreads, we estimate the following regression equation:

$$\Delta CSPRD_{i,t} = \delta + \eta_1 \, \Delta SHORT_{i,t} + \mathbf{\Psi} \, \Delta \mathbf{Z}_{i,t} + \xi_{i,t} \qquad (2)$$

where the dependent variable ($\Delta CSPRD_{i,t}$) is the monthly changes of the credit spread on the bond i at time t, $\Delta SHORT_{i,t}$ is the proxy for the monthly changes of the short interest for firm i at time t, and $\Delta \mathbf{Z}_{i,t}$ is a vector of the control variables for firm i at time t. Following Duffee (1998) and Collin-Dufresne, Goldstein, and Martin (2001), in the main specification, we include as control variables, $\Delta \mathbf{Z}_{i,t}$, the change in the 3-month Treasury bill yield (ΔLEVEL), the change in the 10-year/1-year Treasury yield spread (ΔSLOPE), the change in the Treasury/Eurodollar spread (ΔEURO), the change in the log of bond age (ΔLogAGE), the change in the log of bond maturity (ΔLogMAT), the change in the rolling 12-month stock return volatility (ΔRETVOL), the change in the CBOE's volatility index (ΔVIX), the change in the likelihood of jump[3] (ΔJUMP), and market volatility (MKTVOL). Following Chen, Lesmond, and Wei (2007), we also include annual change in the bond liquidity, which is the fraction of the past twelve months that the bond was traded (ΔLIQ). As noted previously, a concern regarding specification Eq. (2)

is if a spurious correlation in the time-series of credit spread changes and changes in short interest produces these results. Similarly, spurious cross-sectional correlations between credit spread changes and changes of other firm characteristics (such as credit ratings or earnings volatility) could have biased the regression results. To correct for such biases, we estimate Eq. (2) using Newey-West standard errors, Fama-MacBeth regressions, and pure cross-sectional regressions methods. Results in Table VII show increases in short interest lead to significantly larger increases in credit spreads. Using monthly changes of the contemporaneous short interest, we estimate the coefficient estimates to be similar to the baseline case at 0.035 for Newey-West estimates, 0.025 for Fama-McBeth estimates, and 0.134 for cross-sectional estimates. Using monthly changes of the lagged short interest, we similarly estimate the coefficient estimates to be similar to the baseline case at 0.038 for Newey-West estimates, 0.014 for Fama-McBeth estimates, and 0.101 for cross-sectional estimates.

[Insert Table VII here.]

To investigate the impact of short selling on bond portfolio returns, similar to most extant analysis of short selling in equity markets, we estimate a slightly difference variant of the Eq. (2). We estimate the following regression equation:

$$\Delta CSPRD_{i,t} = \delta + \eta_1 \; SHORT_{i,t} + \mathbf{\Psi}\, \Delta\mathbf{Z}_{i,t} + \xi_{i,t} \qquad (4)$$

Again to correct for typical biases, we estimate Eq. (3) using Newey-West standard errors, Fama-MacBeth regressions, and pure cross-sectional regressions methods. Results in Table VIII show increases in short interest lead to significantly larger increases in credit spreads. Using monthly changes of the contemporaneous short interest, we estimate the coefficient estimates at 0.009 for Newey-West estimates, 0.004 for Fama-McBeth estimates, and 0.031 for cross-sectional estimates. Using monthly changes of the lagged short interest, we similarly estimate the coefficient estimates to be similar to the baseline case at 0.008 for Newey-West estimates, 0.004 for Fama-McBeth estimates, and 0.033 for cross-sectional estimates. Except Fama-McBeth estimates, all other estimates are significant at 1%. These results indicate that the impact of large short selling on a particular bond portfolio might smaller than cross-sectional differences large short selling generates across various portfolios.

VII. Conclusion

This paper has examined the relationship between short selling activity in the equity market and bond prices. We provide evidence that the level of short interest is informative regarding credit spreads. Extant research posits that increased short selling reflect information about deteriorating corporate fundamentals. Rising short selling can also indicate an attempt to take advantage of temporary stock price deviations from intrinsic values. Since corporate bond prices should not be affected by equity price deviations from its fair values, then if high short selling activity also affects corporate bond credit spreads, the information content of short interest about fundamentals could be a major reason as to why short selling affects asset prices.

Our analysis provides the first empirical evidence that short selling activity in the equity market conveys negative information about future bond prices. Using a battery of panel regressions, we examine the impact of short interest on credit spreads in a large sample of corporate bond data. We find evidence that otherwise similar corporate bonds carry significantly larger credit spreads when short selling is higher. This finding is robust to the inclusion of various control variables, stratification of the sample, and alternative econometric specifications. Additionally, we document that changes in short interest reliably predict changes in credit spreads, which supports our cross-sectional results. The results suggest that short sellers have fundamental information that affects bond yield spreads. These findings are consistent with the idea that rising short sales indicate the firm is facing or going to face financial difficulties and thus motivate bondholders to sell these bonds. Moreover, we have documented that this relationship shows substantial cross-sectional variation across firms sorted on credit rating and leverage. The relationship between short interest and credit spreads is more pronounced among firms with lower credit ratings and higher leverage.

The results thus bear evidence to the notion that short sellers provide value-relevant information about future fundamental values and therefore the level of short interest is informative regarding not only future equity prices but also bond prices as well. Therefore, our results provide independent verification of the earlier results regarding short sellers' role as detectives of firm value.

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[1] 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, I use simple interpolated fitted Treasury yields for the analysis pursued in the paper.

[2] Other recent studies by, for example, Elton, Gruber, Agrawal, and Mann (2001), Eom, Helwege, and Huang (2004), Gebhardt, Hvidkjaer, and Swaminathan (2005), Guntay and Hackbarth (2007) also rely on the Fixed Income Database.

[3] I follow an estimation procedure similar to that in Collin-Dufresne et al. (2001) to construct the jump probability. I first impute implied volatilities from 1-month out-of-the-money put options and in-the-money call options on the S&P 100 index. I then estimate the OLS parameters of a quadratic regression, $\sigma(K) = a+bK+cK^2$, of implied volatilities $\sigma(K)$ on strike prices K. The JUMP variable is then defined as $\text{JUMP} = \sigma(0.9S) - \sigma(S)$, where S is the level of the S&P 100 index at the time of bond transaction.

Table I
Variable Description and Sample Statistics

This table reports the mean and median of variables in the sample. The sample consists of 62,935 coupon-paying, plain-vanilla corporate bonds of non-financial firms. The data is obtained from the Mergent's FISD database. The sample period covers the years 1994 through 2005. The data for term structure is from Board Governors of Federal Reserve. All accounting data are from the annual COMPUSTAT.

Variable	Description	Mean	Median
CSPRD	The difference between yield to maturity of the corporate bond and corresponding constant maturity Treasury bond	2.147	1.406
CRD	Numerical rating; AAA denoted by one; AA by 2, etc.	3.923	4.000
LEVEL	The yield on 2-year Treasury note	3.508	3.380
SLOPE	The difference between yields on Treasury's 10-year bonds and 2-year notes	1.126	0.983
EUROD	The difference between Eurodollar rate and Treasury's 3-month bill yield	0.264	0.200
AGE	Number of years past issuance	3.532	2.737
MAT	Number of years to maturity	11.293	8.000
RETVOL	The 2-year volatility of monthly equity returns	10.355	9.133
LIQ	number of months the bond traded in past 12 months divided by 12	0.111	0.000
TD2CAP	Total liabilities to market value of equity	2.026	0.968
LTDB	Long-term debt to total assets	0.362	0.342
SIZE	Log of the sum of market value of equity and book value of liabilities	9.438	9.555
EARNVOL	The 5-year volatility of EBITDA to sales	0.031	0.021
QUIK	Cash and receivables to current liabilities	1.665	0.774
ROA	EBITDA to assets	0.135	0.130
INTCOV	EBITDA to interest expense	6.152	4.671
MKTVOL	The 2-year volatility of monthly CRSP market returns	4.467	5.026
JUMP	Probability of jump in stock price	0.350	0.329
VIX	Market volatility index	20.915	20.088
SI	Current month's short interest	2.677	1.650
LAG1SI	Last month's short interest	2.658	1.641
SI1R	Normalized short-sale ranking using all firms	0.678	0.667
LAG1SI1R	Last month normalized short-sale ranking using all firms	0.680	0.667
SI2R	Normalized short-sale ranking using only sample firms	0.499	0.444
LAG1SI2R	Last month normalized short-sale ranking using sample firms	0.499	0.444

Table II
Credit Spreads Across Industries, Ratings, and Other Categories

This table reports mean of credit spreads across years, industries, credit ratings, maturities, firm sizes, and leverage ratios. Firms are separated depending on whether their current month's short interest is above or below median of the sample. The sample consists of 62,935 coupon-paying, plain-vanilla corporate bonds of non-financial firms. The data is obtained from the Mergent's FISD database. The sample period covers the January 1994 through December 2005. The data for term structure is from Board Governors of Federal Reserve. All accounting data are from the annual COMPUSTAT.

	All Firms		Low Current Month's Short Interest		High Current Month's Short Interest	
Categories	NOBS	CSPRD	NOBS	CSPRD	NOBS	CSPRD
Panel A. Industry:						
Consumer Goods	28190	1.953	15215	1.478	12975	2.510
Construction	3853	2.441	1076	2.049	2777	2.594
Steel & Metals	905	2.664	463	2.077	442	3.278
Fabricated Products	599	1.690	415	1.529	184	2.052
Machinery	5329	2.142	2230	1.403	3099	2.673
Auto & Related	9031	2.098	5648	1.402	3383	3.261
Retailers	7978	1.989	3790	1.417	4188	2.507
Others	7050	2.974	2631	2.204	4419	3.433
Panel B. Credit Rating:						
AAA, AA+, AA, AA-	5345	0.727	4943	0.719	402	0.825
A+, A, A-	18608	1.062	13264	1.023	5344	1.159
BBB+, BBB, BBB-	22955	1.726	9252	1.490	13703	1.885
BB+, BB, BB-	8591	3.473	2031	3.192	6560	3.560
B+, B, B-	6440	5.252	1742	5.241	4698	5.256
CCC+ and less	996	8.190	236	8.398	760	8.126
Panel C. Maturity:						
Short-term Bonds	29683	2.301	14083	1.592	15600	2.941
Medium-term Bonds	17055	2.271	7719	1.674	9336	2.764
Long-term Bonds	16197	1.733	9666	1.362	6531	2.282
Panel D. Firm Size:						
Small Firms	18181	3.575	6561	3.250	11620	3.758
Medium Firms	20677	1.929	9000	1.275	11677	2.433
Large Firms	24077	1.255	15907	0.988	8170	1.775
Panel E. Leverage:						
Low Long-term Leverage	25005	1.534	14570	1.179	10435	2.029
Medium Long-term Leverage	19369	2.022	9137	1.545	10232	2.448
High Long-term Leverage	18561	3.102	7761	2.217	10800	3.738

Table III
Univariate Sample Comparison

This table reports the mean values of the variables in the sample across various firm characteristics. Firms are separated depending on whether their current month's short interest (or change in short interest over the past months) is above and below median of the sample. The sample consists of 62,935 coupon-paying, plain-vanilla corporate bonds of non-financial firms. The data is obtained from the Mergent's FISD database. The sample period covers the January 1994 through December 2005. The data for term structure is from Board Governors of Federal Reserve. All accounting data are from the annual COMPUSTAT.

		Current Month's Short Interest				Current Month minus Three Month's Ago Short Interest			
Variable	All Firms (N = 62935)	Low Short Interest (N = 31468)	High Short Interest (N = 31467)	Mean Difference	Mean Comparison p-value	Decreased Short Interest (N = 30171)	Increased Short Interest (N = 32764)	Mean Difference	Mean Comparison p-value
CSPRD	2.147	1.542	2.752	1.210	0.000	2.087	2.201	0.114	0.000
CRD	3.923	3.462	4.384	0.922	0.000	3.902	3.942	0.040	0.000
AGE	3.532	3.735	3.329	-0.406	0.000	3.555	3.511	-0.045	0.073
MAT	11.293	12.239	10.346	-1.893	0.000	11.264	11.319	0.055	0.515
RETVOL	10.355	8.995	11.715	2.720	0.000	10.378	10.334	-0.044	0.293
LIQ	0.111	0.106	0.116	0.009	0.000	0.111	0.111	-0.001	0.728
TD2Cap	2.026	1.712	2.340	0.628	0.000	1.940	2.106	0.166	0.000
LTDB	0.362	0.338	0.386	0.047	0.000	0.360	0.364	0.004	0.001
SIZE	9.438	9.741	9.134	-0.607	0.000	9.478	9.400	-0.078	0.000
EARNVOL	0.031	0.028	0.034	0.005	0.000	0.031	0.031	0.001	0.001
QUIK	1.665	1.562	1.768	0.206	0.000	1.636	1.693	0.057	0.009
ROA	0.135	0.148	0.123	-0.025	0.000	0.136	0.134	-0.002	0.000
SI	2.677	0.920	4.434	3.515	0.000	2.270	3.051	0.781	0.000
lag1SI	2.658	0.963	4.354	3.391	0.000	2.510	2.796	0.286	0.000
SI1R	0.678	0.545	0.810	0.265	0.000	0.644	0.709	0.066	0.000
lag1SI1R	0.680	0.554	0.806	0.252	0.000	0.666	0.692	0.026	0.000
SI2R	0.499	0.242	0.756	0.514	0.000	0.442	0.552	0.111	0.000
lag1SI2R	0.499	0.255	0.743	0.488	0.000	0.476	0.520	0.043	0.000

Table IV
Credit Spreads and Corporate Tax Rates

This table reports results of the regression model of the credit spread using different measures of short sale, a number of control variables, and a host of fixed effects dummy variables. 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. 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 are marked at 1percent, 5 percent, and 10 percent levels with ***, **, and * accordingly.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SI	**0.053*** **	**0.061*** **						
	(4.94)	**(5.00)**						
LAG1SI			**0.048*** **	**0.055*** **				
			(4.52)	**(4.51)**				
SI1R					**0.298** **	**0.519*** **		
					(2.17)	**(3.12)**		
SI2R							**0.161* **	**0.284*** **
							(1.92)	**(3.04)**
CRD	0.266***	0.276***	0.266***	0.278***	0.274***	0.287***	0.274***	0.288***
	(12.37)	(9.60)	(12.30)	(9.60)	(12.24)	(9.43)	(12.23)	(9.39)
LEVEL	-0.452***	-0.455***	-0.455***	-0.457***	-0.455***	-0.460***	-0.454***	-0.459***
	(-16.24)	(-16.43)	(-16.29)	(-16.42)	(-16.29)	(-16.61)	(-16.25)	(-16.54)
SLOPE	-0.663***	-0.665***	-0.662***	-0.664***	-0.669***	-0.674***	-0.667***	-0.672***
	(-15.69)	(-16.04)	(-15.62)	(-15.95)	(-15.81)	(-16.26)	(-15.80)	(-16.25)
EUROD	0.549***	0.539***	0.549***	0.542***	0.549***	0.539***	0.547***	0.537***
	(10.82)	(10.49)	(10.79)	(10.55)	(10.83)	(10.53)	(10.79)	(10.47)
LogAGE	0.101***	0.046***	0.101***	0.047***	0.101***	0.045***	0.101***	0.044***
	(12.63)	(3.77)	(12.70)	(3.78)	(12.49)	(3.52)	(12.47)	(3.44)
LogMAT	0.157***	-0.103	0.158***	-0.101	0.157***	-0.134	0.157***	-0.131
	(9.25)	(-1.22)	(9.26)	(-1.18)	(8.91)	(-1.51)	(8.94)	(-1.46)
RETVOL	0.073***	0.064***	0.074***	0.065***	0.075***	0.065***	0.075***	0.065***
	(6.25)	(6.17)	(6.21)	(6.09)	(6.12)	(6.06)	(6.11)	(6.05)
LIQ	-0.081**	0.018	-0.083**	0.019	-0.084**	0.021	-0.085**	0.021
	(-2.21)	(0.52)	(-2.26)	(0.55)	(-2.24)	(0.62)	(-2.26)	(0.62)
TD2CAP	0.141***	0.117***	0.142***	0.117***	0.149***	0.123***	0.149***	0.123***
	(3.61)	(3.47)	(3.58)	(3.41)	(3.59)	(3.40)	(3.59)	(3.39)

LTDB	1.374***	1.591***	1.375***	1.592***	1.396***	1.612***	1.396***	1.618***
	(2.85)	(3.22)	(2.81)	(3.17)	(2.76)	(3.09)	(2.75)	(3.08)
EARNVOL	-1.181	-0.926	-1.176	-0.907	-1.262	-1.016	-1.282	-1.054
	(-1.26)	(-0.81)	(-1.24)	(-0.78)	(-1.29)	(-0.87)	(-1.30)	(-0.90)
QUIK	-0.092***	-0.102***	-0.092***	-0.103***	-0.089***	-0.099***	-0.089***	-0.099***
	(-3.40)	(-3.00)	(-3.37)	(-2.99)	(-3.18)	(-2.82)	(-3.16)	(-2.79)
ROA	-3.252***	-3.021***	-3.312***	-3.122***	-3.404***	-3.203***	-3.389***	-3.187***
	(-4.44)	(-3.69)	(-4.50)	(-3.81)	(-4.54)	(-3.79)	(-4.50)	(-3.76)
INTD1	0.036	0.047	0.036	0.046	0.023	0.029	0.023	0.028
	(1.06)	(1.31)	(1.07)	(1.31)	(0.67)	(0.79)	(0.67)	(0.76)
INTD2	0.014	-0.005	0.015	-0.004	0.013	-0.006	0.013	-0.006
	(0.72)	(-0.21)	(0.74)	(-0.17)	(0.64)	(-0.25)	(0.65)	(-0.24)
INTD3	0.026**	0.017	0.026**	0.018	0.027**	0.020	0.027**	0.019
	(2.00)	(1.28)	(2.00)	(1.31)	(2.06)	(1.41)	(2.04)	(1.39)
INTD4	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(0.84)	(0.73)	(0.86)	(0.74)	(0.88)	(0.74)	(0.90)	(0.77)
Constant	0.340	0.834	0.351	0.877*	0.170	0.621	0.291	0.822
	(0.92)	(1.61)	(0.95)	(1.67)	(0.43)	(1.12)	(0.77)	(1.53)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	-	Yes	-	Yes	-	Yes	-
Bond dummy	-	Yes	-	Yes	-	Yes	-	Yes
N.Obs.	62791	62791	62591	62591	62791	62791	62791	62791
Adj. RSQ.	0.7603	0.7899	0.7599	0.7893	0.7580	0.7876	0.7579	0.7875

Table V
Credit Spreads and Short Interest Across Sub-Samples

This table reports the results of the robustness regression models of the credit spread using various measures of short sale (short interest) across different credit rating, bond maturity, firm size, and firm long-term leverage categories. 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 small-cap, mid-cap, and long-cap, if the ratio of its long-term debt to total assets is, respectively, in the bottom, middle, and top thirds of the COMPUSTAT universe. A firm is denoted as small-cap, mid-cap, and long-cap, if the natural log of the sum of its market value equity plus book value of debt is, respectively, in the bottom, middle, and top thirds of the COMPUSTAT universe. Robust (heteroskedasticity, autocorrelation, and firm-clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero are marked at 1 percent, 5 percent, and 10 percent levels with ***, **, and * accordingly.

Panel A.

	AAA – AA Rated	A – BBB Rated	BB – C Rated	Short-term Bond	Mid-term Bond	Long-term Bond
SI	0.011	0.039***	0.034***	0.073***	0.022	0.073***
	(0.41)	(2.82)	(2.74)	(4.27)	(1.56)	(5.27)
N.Obs.	5338	41478	15975	29629	16998	16164
Adj. RSQ.	0.2616	0.3637	0.4946	0.6447	0.6555	0.5421
LAG1SI1	-0.000	0.037**	0.032**	0.069***	0.020	0.072***
	(-0.01)	(2.54)	(2.52)	(3.92)	(1.46)	(5.08)
N.Obs.	5326	41376	15889	29518	16943	16130
Adj. RSQ.	0.2604	0.3648	0.4943	0.6448	0.6552	0.5420
SI1R	0.131	0.465***	0.510*	0.462**	0.303*	0.549***
	(0.98)	(3.69)	(1.74)	(2.14)	(1.67)	(3.17)
N.Obs.	5338	41478	15975	29629	16998	16164
Adj. RSQ.	0.2622	0.3631	0.4923	0.6370	0.6551	0.5318
SI2R	0.008	0.172**	0.137	0.124	0.054	0.190*
	(0.09)	(2.08)	(0.73)	(0.95)	(0.52)	(1.79)
N.Obs.	5338	41478	15975	29629	16998	16164
Adj. RSQ.	0.2615	0.3602	0.4911	0.6361	0.6544	0.5292

Panel B.

	Small-Cap Firms	Mid-Cap Firms	Large-Cap Firms	Low Leverage	Medium Leverage	High Leverage
SI	0.019	0.030**	0.135***	0.033*	0.004	0.076**
	(1.59)	(2.17)	(4.35)	(1.75)	(0.36)	(2.42)
N.Obs.	18113	20635	24043	24954	19323	18514
Adj. RSQ.	0.5630	0.6740	0.4940	0.5271	0.6012	0.6486
LAG1SI1	0.016	0.030**	0.129***	0.027	0.002	0.075**
	(1.35)	(2.26)	(4.25)	(1.52)	(0.17)	(2.33)
N.Obs.	18031	20577	23983	24883	19258	18450
Adj. RSQ.	0.5631	0.6743	0.4931	0.5257	0.6027	0.6491

SI1R	0.061	0.821***	0.691***	0.366*	0.079	0.339
	(0.28)	(3.40)	(3.30)	(1.90)	(0.37)	(1.01)
N.Obs.	18113	20635	24043	24954	19323	18514
Adj. RSQ.	0.5621	0.6762	0.4737	0.5258	0.6012	0.6394
SI2R	-0.117	0.340**	0.319**	0.061	-0.090	0.114
	(-0.88)	(2.38)	(2.47)	(0.52)	(-0.63)	(0.55)
N.Obs.	18113	20635	24043	24954	19323	18514
Adj. RSQ.	0.5623	0.6740	0.4707	0.5243	0.6013	0.6391

Table VI
Robustness Regressions for Credit Spreads and Short Interest

This table reports results of the robustness regression models of credit spread using various measures of short sale (short interest) 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 (heteroskadasticity, autocorrelation, and firm clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero at 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

	Newey-West Standard Errors	Fama-McBeth Regression	Cross-Sectional Regression	Newey-West Standard Errors	Fama-McBeth Regression	Cross-Sectional Regression
SI	**0.058*** **	**0.030*** **	**0.063*** **			
	(14.80)	**(6.19)**	**(10.88)**			
LAG1SI				**0.054*** **	**0.029*** **	**0.064*** **
				(14.08)	**(6.02)**	**(11.40)**
CRD	0.266***	0.273***	0.294***	0.266***	0.273***	0.293***
	(81.89)	(36.41)	(32.13)	(81.86)	(36.34)	(32.09)
LEVEL	-0.074***	-0.814***	-0.105**	-0.075***	-0.828***	-0.107**
	(-9.91)	(-4.64)	(-2.52)	(-10.12)	(-4.75)	(-2.57)
SLOPE	-0.035**	-0.418*	0.179*	-0.039**	-0.436**	0.173*
	(-2.23)	(-1.96)	(1.85)	(-2.50)	(-2.01)	(1.81)
EUROD	0.032	0.116	0.277	0.028	0.147	0.255
	(0.81)	(0.52)	(1.03)	(0.71)	(0.66)	(0.97)
LogAGE	0.125***	0.119***	0.215***	0.125***	0.120***	0.213***
	(27.54)	(23.45)	(11.94)	(27.52)	(23.38)	(11.89)
LogMAT	0.134***	0.179***	0.117***	0.135***	0.180***	0.121***
	(17.42)	(11.60)	(4.08)	(17.53)	(11.71)	(4.24)
RETVOL	0.132***	0.090***	0.117***	0.134***	0.091***	0.119***
	(51.33)	(25.39)	(22.02)	(52.36)	(25.98)	(22.38)
LIQ	-0.303***	-0.387***	-1.594***	-0.304***	-0.387***	-1.642***
	(-11.11)	(-9.26)	(-6.81)	(-11.12)	(-9.24)	(-7.06)
TD2CAP	0.072***	0.076***	0.085***	0.072***	0.077***	0.085***
	(19.07)	(11.63)	(17.88)	(19.02)	(11.56)	(17.83)
LTDB	1.209***	1.047***	1.017***	1.215***	1.047***	1.005***
	(18.68)	(16.15)	(6.72)	(18.72)	(16.25)	(6.64)
EARNVOL	0.610**	0.366	0.848	0.473*	0.252	0.560
	(2.36)	(1.29)	(1.46)	(1.83)	(0.88)	(0.97)
QUIK	-0.046***	-0.031***	-0.051***	-0.046***	-0.030***	-0.050***
	(-18.45)	(-11.51)	(-6.29)	(-18.18)	(-11.32)	(-6.20)
ROA	-1.992***	-1.193***	-3.331***	-1.993***	-1.188***	-3.215***
	(-14.37)	(-7.82)	(-7.91)	(-14.35)	(-7.74)	(-7.66)
INTD1	0.018**	-0.009	-0.064***	0.022**	-0.005	-0.060**
	(2.08)	(-0.73)	(-2.66)	(2.46)	(-0.46)	(-2.54)
INTD2	0.079***	0.089***	0.144***	0.078***	0.088***	0.139***
	(16.04)	(14.94)	(6.81)	(15.83)	(14.71)	(6.63)
INTD3	0.018***	0.018***	0.010	0.018***	0.018***	0.010

	(6.34)	(2.77)	(0.63)	(6.31)	(2.80)	(0.63)
INTD4	0.011***	-0.015	0.007	0.011***	-0.010	0.008
	(5.99)	(-0.19)	(1.06)	(6.04)	(-0.12)	(1.21)
Constant	-2.732***	0.511	-2.404***	-2.747***	0.509	-2.418***
	(-33.53)	(0.58)	(-6.89)	(-33.64)	(0.58)	(-6.99)
N.Obs.	62791	62791	3503	62591	62591	3500
Adj. RSQ.	0.6237	0.6769	0.7358	0.6237	0.6769	0.7372

Table VII
Robustness of Relation between the Monthly Changes in Short Interest

This table reports the results of the regression models of the monthly changes in the credit spread. 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 3,188 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 are marked at 1 percent, 5 percent, and 10 percent levels with ***, **, and * accordingly.

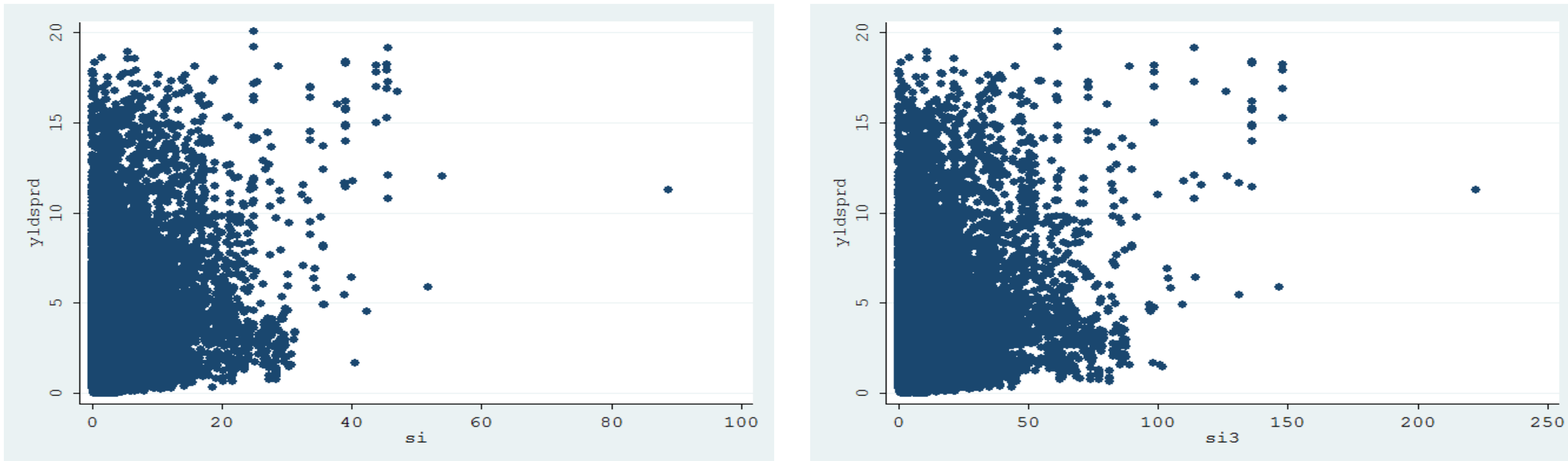
	Newey-West Standard Errors	Fama-McBeth Regressions	Cross-Sectional Regression	Newey-West Standard Errors	Fama-McBeth Regressions	Cross-Sectional Regression
ΔSI	**0.035*** **	**0.025*** **	**0.134*** **			
	(2.88)	**(3.10)**	**(18.84)**			
ΔLAG1SI1				**0.038*** **	**0.014* **	**0.101*** **
				(3.58)	**(1.93)**	**(16.00)**
ΔCRD	0.235***	0.155***	0.513***	0.233***	0.164***	0.532***
	(10.69)	(6.99)	(15.91)	(10.64)	(7.28)	(15.93)
ΔLEVEL	-0.361***	-0.496***	-0.462***	-0.362***	-0.505***	-0.466***
	(-18.21)	(-11.95)	(-5.08)	(-18.15)	(-11.93)	(-5.03)
ΔSLOPE	-0.518***	-0.664***	-0.533***	-0.519***	-0.659***	-0.473***
	(-18.83)	(-8.21)	(-3.48)	(-18.90)	(-8.23)	(-3.02)
ΔEUROD	0.140***	0.372***	1.351***	0.142***	0.376***	1.556***
	(4.47)	(4.03)	(7.68)	(4.55)	(3.91)	(8.18)
ΔLogAGE	0.005	0.076***	0.005	0.008	0.079***	0.015
	(0.76)	(2.99)	(0.22)	(1.16)	(2.97)	(0.62)
ΔLogMAT	-0.423***	0.051	-2.608***	-0.417***	0.058	-2.681***
	(-3.25)	(0.49)	(-13.28)	(-3.19)	(0.56)	(-13.37)
ΔRETVOL	0.061***	0.045***	0.071***	0.068***	0.050***	0.082***
	(6.99)	(4.47)	(8.72)	(7.48)	(4.89)	(9.13)
ΔVIX	0.033***	0.029***	0.041***	0.033***	0.027***	0.041***
	(24.33)	(5.31)	(5.28)	(24.59)	(4.99)	(5.34)
ΔJUMP	-0.056***	-0.131	-0.518**	-0.058***	-0.124	-0.192
	(-2.71)	(-1.01)	(-2.45)	(-2.83)	(-0.95)	(-0.93)
MKTVOL	-0.003	0.063	0.004	-0.004	0.018	0.009
	(-1.05)	(0.71)	(0.33)	(-1.24)	(0.20)	(0.68)
ΔLIQ	0.014	0.024	-0.637	0.012	0.026	-0.215
	(0.94)	(1.30)	(-1.57)	(0.84)	(1.29)	(-0.66)
Constant	0.022	-0.404	-0.095	0.025*	-0.166	-0.118**
	(1.60)	(-0.93)	(-1.61)	(1.83)	(-0.38)	(-1.97)
N.Obs.	55893	55893	3188	55617	55617	3176
Adj. RSQ.	0.0854	0.1609	0.5192	0.0871	0.1577	0.5092

Table VIII
Robustness of Relation between Short Interest and the Monthly Changes in Credit Spreads

This table reports the results of the regression models of the monthly changes in the credit spread. 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 3,188 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 are marked at 1 percent, 5 percent, and 10 percent levels with ***, **, and * accordingly.

	Newey-West Standard Errors	Fama-McBeth Regressions	Cross-Sectional Regression	Newey-West Standard Errors	Fama-McBeth Regressions	Cross-Sectional Regression
SI	**0.009*** **	**0.004**	**0.031*** **			
	(2.64)	**(1.28)**	**(9.46)**			
LAG1SI1				**0.008** **	**0.004**	**0.033*** **
				(2.30)	**(1.29)**	**(9.93)**
ΔCRD	0.243***	0.162***	0.688***	0.243***	0.164***	0.676***
	(10.43)	(7.09)	(21.74)	(10.42)	(7.04)	(21.25)
ΔLEVEL	-0.366***	-0.522***	-0.355***	-0.368***	-0.525***	-0.355***
	(-18.24)	(-11.58)	(-3.76)	(-18.27)	(-11.66)	(-3.76)
ΔSLOPE	-0.518***	-0.679***	-0.053	-0.519***	-0.675***	-0.055
	(-18.84)	(-8.35)	(-0.34)	(-18.88)	(-8.39)	(-0.35)
ΔEUROD	0.140***	0.401***	1.688***	0.140***	0.388***	1.690***
	(4.48)	(4.16)	(9.28)	(4.49)	(4.02)	(9.28)
ΔLogAGE	0.003	0.070***	-0.008	0.005	0.070***	-0.007
	(0.47)	(2.70)	(-0.31)	(0.69)	(2.69)	(-0.30)
ΔLogMAT	-0.426***	0.031	-2.601***	-0.423***	0.044	-2.566***
	(-3.22)	(0.30)	(-12.70)	(-3.19)	(0.42)	(-12.52)
ΔRETVOL	0.063***	0.049***	0.074***	0.066***	0.049***	0.074***
	(7.09)	(4.76)	(8.73)	(7.47)	(4.90)	(8.76)
ΔVIX	0.033***	0.023***	0.019**	0.033***	0.023***	0.021***
	(24.24)	(4.01)	(2.44)	(24.28)	(3.95)	(2.63)
ΔJUMP	-0.055***	-0.081	-0.436**	-0.057***	-0.081	-0.420*
	(-2.64)	(-0.64)	(-1.98)	(-2.73)	(-0.63)	(-1.91)
MKTVOL	-0.004	0.032	-0.020	-0.004	0.048	-0.020
	(-1.21)	(0.36)	(-1.56)	(-1.29)	(0.54)	(-1.51)
ΔLIQ	0.014	0.022	-0.640	0.012	0.022	-0.786*
	(0.98)	(1.18)	(-1.52)	(0.83)	(1.14)	(-1.81)
Constant	0.003	-0.277	-0.075	0.007	-0.323	-0.079
	(0.19)	(-0.63)	(-1.20)	(0.45)	(-0.72)	(-1.27)
N.Obs.	55893	55893	3188	55781	55781	3185
Adj. RSQ.	0.0834	0.1670	0.4801	0.0837	0.1656	0.4810

Panel A.



Panel B.

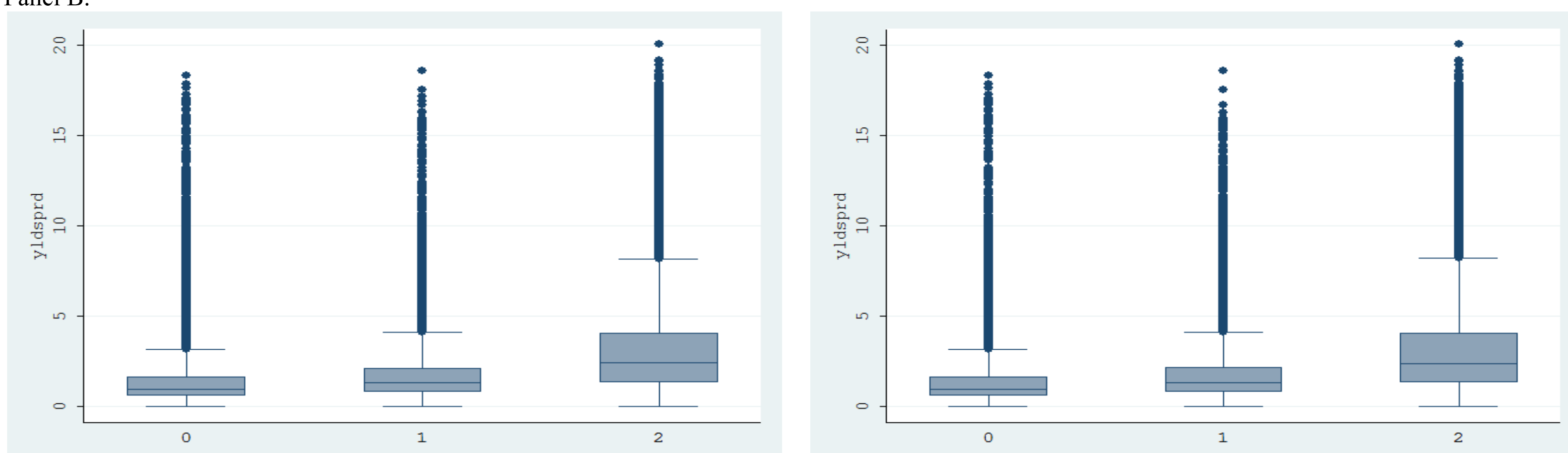


Figure 1. Credit spreads and the corporate tax rate. Panel A plots credit spreads and short interest. Panel B box-plots the distribution of credit spreads across different levels of the short interest. The 25th – 75th percentiles are limits of the gray box with the median shown by a line in the middle. The outliers beyond 99th are shown with diamonds.