Un journal de asfae chile

mbr Multidisciplinary Business Review

EQUITY SHORT SELLING AND THE COST OF DEBT*

VENTA CORTA DE ACCIONES Y EL COSTO DE LA DEUDA

Ali Nejadmaleyeri[a] • Bilal Erturk[b]

Classification: Empirical paper – research
Received: April 11, 2020 / Revised: July 14, 2020 / Accepted: August 26, 2020

Abstract

Empirical evidence suggests that short sales have pertinent information about firm fundamentals. If so, then information from short selling in liquid equity markets can be informative for infrequently traded corporate bonds. The adverse information conveyed by short interest should mean higher cost of debt. Using a large sample of corporate bonds, we examine whether lagged equity short interest affects credit spreads. Highly shorted firms do experience wider credit spreads in the subsequent months. Moreover, the increase in short interest leads to higher credit spreads. Short interest thus seems to contain adverse information about firm fundamentals that can prove useful to bond investors.

Keywords: short selling, cost of debt, credit spread.

Resumen

La evidencia empírica sugiere que las ventas cortas tienen información pertinente sobre los fundamentos de la empresa. Si es así, la información de las ventas cortas en los mercados accionarios líquidos puede ser informativa para los bonos corporativos que se transan infrecuentemente. La información adversa que transmite el interés corto debería significar un mayor costo de la deuda. Utilizando una muestra grande de bonos corporativos, examinamos si los intereses cortos de las acciones rezagados afectan los diferenciales crediticios. Las empresas con altas posiciones cortas experimentan márgenes crediticios más amplios en los meses siguientes. Además, el aumento de los tipos de interés a corto plazo se traduce en mayores diferenciales de crédito. Por tanto, el interés corto parece contener información adversa sobre los fundamentos de la empresa que pueden resultar útiles para los inversionistas en bonos.

Palabras clave: ventas en corto, costo de la deuda, margen crediticio.

[a] Corresponding author. John A. Guthrie Endowed Chair in Banking and Financial Services. Department of Accounting and Finance. College of Business, University of Wyoming, Laramie, WY, USA. Email: anejadma@uwyo.edu
[b] Mays Business School, Department of Finance. Texas A&M University, College Station, TX, USA. Email: berturk@mays.tamu.edu
* I would like to thank Tim Krehbiel, Sattar Mansi, John Polonchek, and the seminar participants in 2012 Midwestern Finance Association meetings, as well as the 2014 European Financial Management Association meeting for helpful comments.

Introduction

In their influential work, Diamond and Verrecchia (1987) argue that since short sellers cannot use sale proceeds, they are not short for liquidity reasons, implying that short sellers primarily trade based on information. Empirical evidence supports the idea that short sellers are, on average, well-informed and anticipate negative stock returns and corporate events.[1] Given that short sellers uncover value-relevant information about firms, and thus add to the information efficiency of equity prices, an interesting question arises: can equity short sales matter for valuation of corporate securities other than equity, per se, corporate bonds where illiquidity hinders the ability of trading to compound information onto prices?

We address this question by examining the relationship between short selling in the equity market and corporate bond prices. Using a large panel of plain vanilla (i.e., no option features) corporate bonds from nonfinancial U.S. firms for the period of January 1994 to December 2019, we examine whether short interest is interpreted as negative news in the bond market and find consistent evidence. Bonds of firms with higher short interest tend to trade with higher credit spreads in the subsequent one and three months than otherwise similar firms. We find that each additional percentage of short interest results in more than 2 basis points greater credit spread relative to otherwise similar firms, depending on model specification. Our tests suggest that short sellers contribute to more efficient pricing of corporate bond securities.

We examine the informational role of short selling from bondholders' perspectives for two reasons. First, corporate bond markets are quite illiquid (Warga, 1992). Lack of liquidity and infrequent trading limit the extent to which information can flow through bond prices. This can be a particularly acute problem for bondholders who care greatly about default risk. Since adverse changes to firms' fortunes are rare occurrences, the information about such events from a timely source, per se, short selling activity, can prove critical.

Second, our analysis focuses on bond credit spreads for a broad universe of firms with public corporate debt in order to examine whether the information short sellers utilize is relevant, not only for equity securities, but for overall firm value. Corporate bond prices (credit spreads) are correlated with earnings and cash flows (Callen, Livnat, & Segal, 2009). To the extent that short selling in the equity market signals bad news about a firm's prospects, the level of short interest should contribute to the pricing of corporate bonds and be adversely related to its credit spread. Thus, our analysis sheds light on the information value of equity short sales on firm fundamental value.

Our analysis indeed reveals interesting regularities. We find that the informativeness of short selling is greater for riskier firms. Specifically, bond investors place greater value on short-interest information when pricing bonds of firms with lower credit ratings, higher leverage, and greater volatility. We also observe that the impact of short interest is more pronounced for firms with more insider/executive selling. We further demonstrate the robustness of our results by examining the effect of policy uncertainty. Even controlling for policy uncertainty, we still find that lagged rising short interests extenuate corporate credit spreads.

Our results also expand the extant literature on short selling that envisions short sellers as sophisticated investors and document that short interest or shorting flow correctly predicts negative future abnormal stock returns. Diether, Lee, and Werner (2009) and Boehmer et al. (2008) find that short-selling flow predicts future negative abnormal returns. Dechow et al. (2001), Desai et al. (2002), and Asquith, Pathak, and Ritter (2005), among others, provide evidence of a negative relationship between short interest and subsequent stock returns. Higher short interest could be informative for future stock returns if it proxies for additional market frictions or if it signals informed trading. If high short interest proxies for stock overpricing due to short-selling constraints, it may predict future stock returns (Jones & Lamont, 2002; Miller, 1977). Short sales may also predict subsequent stock returns because short sellers trade on value-relevant information; and their positions reveal adverse information, thus moving prices toward fundamental value (Cohen, Diether, & Malloy, 2007).

Our findings are also supported by earlier works that explore specific corporate events in order to show that short sellers may also be informed about future firm fundamentals. Prior studies find that short sellers target firms with financial misconduct (Karpoff & Lou, 2010), poor earnings quality (Desai, Krishnamurthy, & Venkataraman, 2006), and high accruals (Hirshleifer, Teoh, & Yu, 2011), as well as firms experiencing negative earnings surprises (Christophe et al., 2004) and analyst downgrades (Christophe et al., 2010). Our approach of

1 Boehmer, Jones, and Zhang (2008) find that as a group, short sellers are quite informed, and institutional nonprogram short sales are particularly informative about future negative returns. Short sellers appear to use fundamental analysis to predict abnormal negative equity returns (Dechow, Hutton, Meulbroek, & Sloan, 2001; Desai, Ramesh, Thiagarajan, & Balacahandran, 2002). Moreover, short selling increases prior to major events such as unfavorable earning announcements (Christophe, Ferri, & Angel, 2004), stock analyst downgrades (Christophe, Ferri, & Hsieh, 2010), bond rating downgrades (Henry, Kisgen, & Wu, 2010), and SEC enforcement action on financial statement misrepresentation (Karpoff & Lou, 2010).

Multidiscip. Bus. Rev. | *Vol. 13, N° 2, 2020, pp. 41-53, ISSN 0718-400X*
DOI: *https://doi.org/10.35692/07183992.13.2.5*

using bond prices has one advantage over the preceding works that use specific corporate events. We use transaction prices observed in the bond market that reflect the overall evaluation of short sales by the bond investors rather than studying each corporate event separately in order to detect information from short selling about fundamentals. Given the disappointing performance of extant structural models of bond pricing in explaining observed data (Eom, Helwege, & Huang, 2004), empirical models seek variables not considered by the theory that can improve the explanatory power. Our results suggest that short selling is correlated with omitted variables pertinent to pricing corporate bonds.

Related Literature

A broadening base of empirical research demonstrates 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 suggests that a short seller is relatively more informed than an average investor. As sophisticated investors, short sellers should have superior analytical skills in 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." High short interest thus would convey adverse information.

The extant literature on short selling documents that short interest is negatively related to future stock returns. Desai 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. The literature offers two reasons to explain this. High short interest indicates market frictions that cause stock overpricing, implying a negative association between short interest and subsequent stock returns consistent with Miller (1977). Asquith et al. (2005) argue that restrictions in the market for borrowing shares may cause a stock to be overvalued and generate low subsequent 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) and Boehme, Danielsen, and Sorescu (2006) find underperformance among stocks with high shorting costs.

Short interest can also convey adverse information about firm fundamentals. Cohen et al. (2007) contend that shorting demand signals informed trading. They show that stock returns are only predicted by changes in shorting demand, not shorting supply. Boehmer et al. (2008) 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. Diether et al. (2009) find that short sellers are successful in detecting short-term deviations of stock prices from fundamental value due to market frictions and by targeting overpriced stock profits from their trades. Dechow et al. (2001) document that short sellers target firms that price high relative to earnings or book value and unwind their positions as these ratios mean-revert, thereby earning above-normal returns. They advocate that short sellers take positions in stocks they believe to be temporarily overpriced. In sum, the literature posits that short sellers are highly informed traders targeting overpriced stocks. Empirical work so far has not examined whether the pricing implications of short selling transcend the equity markets. In this paper, we posit that by investigating the informativeness of short interest from the perspective of bond investors, we can determine the importance of the value-relevant information content of aggregate short selling.

Another line of research explores the ability of short sellers to predict corporate events. For example, Christophe et al. (2004) show that negative earnings surprises are preceded by unusually high short-selling activity. Desai et al. (2006) show that short sellers can identify and take positions in firms that announce earnings restatements and subsequently unwind their positions. Karpoff and Lou (2010) demonstrate that short sellers anticipate the discovery and severity of financial misconduct. Christophe et al. (2010) document abnormally high short selling prior to analyst downgrades. They also find that the level of short selling is especially higher for firms with more negative event abnormal returns. Overall, the extant literature leads to the following hypotheses:

H1. If higher short-selling indicates greater adverse information about the business fundamentals, the larger the short-interest, the wider the credit spread will be.

H2. If higher short-selling indicates greater adverse information about the business fundamentals, the larger the short-interest corresponds to widen the credit spread, especially for riskier firms (lower credit rating, higher leverage, greater volatility, and more CEO share-selling).

Empirical Methodology

Following the trains of thought 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

Multidiscip. Bus. Rev. | *Vol. 13, N° 2, 2020, pp. 41-53, ISSN 0718-400X*
DOI: *https://doi.org/10.35692/07183992.13.2.5*

in the paper is a panel regression ordinary least squares (OLS) model as follows.

$$CSPRD_{i,t} = \alpha + \beta_1 SHORT_{i,t-1} + \ddot{O}\boldsymbol{X}_{i,t} + \mu_{i,t} \quad (1)$$

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 $\boldsymbol{X}_{i,t}$ is a vector of control variables for firm i at time t. The explanatory variables in $\boldsymbol{X}_{i,t}$ 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. The baseline model includes industry-level and firm-level dummies to ensure that the results regarding the relationship between short-selling activity in the equity market and credit spreads are not largely due to spurious cross-sectional correlations between credit spreads and other bond and firm characteristics. Lastly, to control for the impact of time-series correlation on residuals, we re-estimate our baseline model in three alternative ways: panel regression with Newey-West standard errors, Fama-MacBeth regressions, and pure cross-sectional regressions of time-series averages.

Dependent Variables: 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.[2]

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 as reported by the exchanges (NYSE, NASDAQ, and AMEX) divided by the total number of shares outstanding of a particular firm. Since we investigate the pricing implications of short selling on corporate bonds, we examine the behaviour of bond prices *after* short-selling activity is observed. The short-interest variable is measured one month (LAG1SI) and three months (LAG3SI) before the credit spread variable is measured, consistent with the existing literature such as Asquith et al. (2005) and Dechow et al. (2001), among others. Using credit spreads one and three months after short selling activity in the equity market is observed allows us to test whether investors drive up yields on corporate bonds in response to higher equity short sales relative to otherwise similar bonds.

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 variable. 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 et al. (2001), Campbell and Taksler (2003), Chen, Lesmond, and Wei (2007), Nejadmalayeri and Singh (2012), and Nejadmalayeri, Singh, and Mathur (2013). 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 1 below provides a list of all variables with brief descriptions. These variables are defined as follows.

Credit Quality

As with Collin-Dufresne et al. (2001) and Chen et al. (2007), we use the numerical rating CRD as a determinant of credit spreads. We follow the COMPUSTAT convention to assign numerical values for different ratings. So, for instance, a value of 2 denotes a AAA rating whereas a value 4 denotes an A rating. We use the average of Moody's rating and Standard and Poor's (S&P) rating unless one is not available, in which case the available rating is used. We also add a modified version of Altman's (1968) Z-score which does not included leverage.

Treasury Term Structure and Liquidity

In structural models of credit risk, a rise in the risk-free rate effectively reduces the likelihood of default (Leland, 1994; Longstaff & Schwartz, 1995). Previous empirical studies (Chen et al., 2007; Duffee, 1998) indicate that credit spreads tend to fall when Treasury yields rise. As such, we use the one-year Treasury bill yield, LEVEL, as a determinant of credit spreads. The slope of the term

2 Although other more sophisticated methods can be used to find the fitted Treasury yield curve, Elton, Gruber, Agrawal, and Mann et al. (2001) note that these different proxies yield qualitatively similar results. Therefore, we use simple interpolated fitted Treasury yields for the analysis pursued in this paper.

structure of the Treasury interest rates seems to have explanatory power in predicting both interest rate movements and macroeconomic growth (Litterman & 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 two-year constant maturity bonds' yields, SLOPE, as a determinant of credit spreads. As with Chen et al. (2007), we use the spread between the three-month Euro-dollar rate and the three-month Treasury bill yield, EURO, to capture the Treasury bonds' "crowding out" adverse liquidity effect.

Bond Age and Maturity

Bond age has been shown to relate positively to credit spreads (see Nejadmalayeri & Singh, 2012; Nejadmalayeri et al., 2013; Perraudin & Taylor, 2004; Warga, 1992). 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. 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.

Bond Liquidity

Recent work indicates that liquidity is a priced risk in corporate bonds' credit spreads (Chen et al., 2007; Covitz & Downing, 2007). We use the Güntay and Hackbarth (2010) 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 in order to standardize the measure to the unit interval.

Profitability and Quick Ratio

Firms with a higher operational income can meet their debt service more easily and hence are less likely to default in the near future. We use the ratio of earnings before tax and depreciation divided by book value of total assets, ROA. In the 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, QUIK.

Volatility

Structural models also predict that the volatility of firm value is positively related to credit spreads (see Acharya & Carpenter, 2002; Leland, 1994; Longstaff & Schwartz, 1995;). 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. 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 the expected riskiness of the future earnings stream. Specifically, we use the five-year standard deviation of ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to assets.

Leverage and Debt Service

Default risk, or the ability to meet 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 with Chen et al. (2007), we use the ratio of the book value of total liabilities to market value of equity, TD2CAP. Additionally, we use the ratio of long-term debt to total book-value of assets, LTDB. The ability to meet periodic debt service is the first test in determining whether a borrower is at default. 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).

Data and Summary Statistics

Data

We start with all bonds of U.S. corporations that can be identified in the Fixed Income Securities Database (FISD) as provided by Wharton Research Data Services (WRDS) for the period of January 1996 to December 2003 in order to construct a sample of potential corporate bonds. We amend the sample with all bonds with valid data in the Trade Reporting and Compliance Engine (TRACE) system from 2004 onward.[3] As is the convention

3 Mergent Fixed Income Securities Database (FISD) reports transaction data from the National Association of Insurance Commissioners (NAIC), and therefore only trades conducted by insurance companies are included. Insurance companies are the most prominent investors in corporate bonds (Campbell & Taskler, 2003). Other recent studies by, for example, Elton et al. (2001), Eom et al. (2004), Gebhardt, Hvidkjaer, and Swaminathan (2005), and Güntay and Hackbarth (2010) also rely on FISD. However, since 2002, the FISD data is supplemented with transactions reported to the TRACE provided by the Financial Industry Regulatory Authority (FINRA). Introduced in 2002, TRACE reports tick-by-tick transaction data for all U.S. corporate bonds and, as of 2005, approximately 99% of all public bond transactions are reported.

Multidiscip. Bus. Rev. | *Vol. 13, N° 2, 2020, pp. 41-53, ISSN 0718-400X*
DOI: *https://doi.org/10.35692/07183992.13.2.5*

of the literature, we exclude all bonds with option-like features such as callibility, putability, convertibility, and sinking fund provisions. Following extant literature (Chen et al., 2007; Collin-Dufresne et al., 2001; Nejadmalayeri & Singh, 2012; Nejadmalayeri et al., 2013), we use a number of independent variables as typical control determinants of credit spreads with macroeconomic factors (i.e., Treasury term structure and Euro-dollar rate), stock-related attributes (i.e., stock return volatility and total liability to capital), and accounting characteristics (i.e., leverage, liquidity, business risk). The filtered data is then merged with Treasury term structure information from the Fed. Next, we merge the data with data from monthly CRSP. We use monthly CRSP to obtain stock prices, stock return volatility, and market volatility. We use the COMPUSTAT annual database to obtain accounting information about each firm such as leverage, interest coverage, quick ratio, profitability, and earnings volatility. We require firms to have valid accounting measures in the year prior to the transaction. Some accounting characteristics are, however, multiyear averages. In general, for a firm to be considered, accounting information must be available for at least three years prior to the transactions. We also use ExecuCOMP data to obtain information about the chief executive's stock and option holdings. We then delete any nonrated bond. 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). Lastly, we merge our data with monthly short-interest data provided from exchanges. This leaves us with a final sample of 213,754 bond-month observations that come from 5,483 firms with an average of five bonds per firm and an average of 39 observations per bond.

Summary Statistics

Table 1 provides summary descriptive statistics for the variables employed in the analysis. The mean credit spread for the sample of new bond issues is 1.868%. The mean two-year T-bill yield at the time of issue is 1.559%, and the mean difference between 10- and two-year T-bond yields at the time of issue for the sample is 1.358%. Duffee (1998) shows that, on average, credit spreads are between 0.67% to 1.42% centred 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. More recently, Nejadmalayeri and Singh (2012) report an average credit spread of 2.162 for the period of 1994-2006.

The sample characteristics used here are somewhat comparable with previous studies (see Collin-Dufresne et al., 2001; Elton et al. 2001). Firms in our sample generate a return on assets of 1.389%. The mean long-term debt ratio for the sample firms is about 31.7%. Overall, firms in the sample are large, profitable firms with relatively low leverage. For our sample of bonds, the mean years-to-maturity is 9.921, which is comparable to the samples in previous empirical studies. The mean short interest in our sample is 4.139%, which is comparable to previous studies such as Asquith et al. (2005).

Univariate Analyses and Sample Comparisons

To gain insight into the relationship between short interest and expected credit spreads, we examine their univariate relationship in the cross-section and over time. Our sample comparisons confirm the basic idea that higher short interest leads to larger credit spreads. The unconditional credit spread difference between high and low short interest firms is 0.797% and highly statistically significant, as reported in Table 2. Short interest is higher for firms with greater risk. For instance, while high short-interest firms have an average credit rating of 10.601, low short-interest firms have an 8.843 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 2.9% more long-term leverage, 1.6% more stock return volatility, and 3.2% less interest coverage.

Multivariate Results

As discussed previously, we estimate a reduced-form empirical model of credit spreads that, in essence, is a linear regression of credit spreads on short interest (on a one-month or three-month lagged basis) and common control variables. We first begin to run a series of panel regressions, with robust (heteroskedasticity, autocorrelation, and firm-clustering corrected) standard errors and different fixed effects, to illustrate the relationship 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. 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, Fama-MacBeth, and cross-sectional regressions. To examine the nonlinearity of the impact of variables such as ratings, volatility, firm size, and leverage, we then stratify the panel into subsets of firms and re-estimate the baseline model. This demonstrates that our main findings

Table 1. Variable Description and Sample Statistics

This table reports the mean and median of variables in the sample. The sample consists of 213,754 coupon-paying, plain-vanilla corporate bonds of nonfinancial firms. The data is obtained from the Mergent's FISD database. The sample period covers the period of January 1994 through December 2019. 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	1.868	1.442
CRD	Numerical rating; AAA denoted by one; AA by 2, etc.	9.723	10.000
ZSCORE†	The traditional Altman (1968) Z-score without leverage	1.559	1.546
LEVEL	The yield on 2-year Treasury note	1.358	0.450
SLOPE	The difference between yields on Treasury's 10-year bonds and 2-year notes	1.516	1.586
EUROD	The difference between Eurodollar rate and Treasury's 3-month bill yield	0.396	0.273
AGE	Number of years past issuance	4.044	3.000
MAT	Number of years to maturity	9.921	7.000
LIQ	Natural log of total dollar (in $M) traded during the month	0.014	0.017
RETVOL	The 2-year volatility of monthly equity returns	0.078	0.068
EARNVOL	The 5-year volatility of EBITDA to sales	0.148	0.077
TD2CAP	Total liabilities to market value of equity	1.000	0.637
LTDB	Long-term debt to total assets	0.317	0.297
QUIK	Cash and receivables to current liabilities	0.142	0.140
ROA	EBITDA to assets	1.389	0.857
INTCOV	EBITDA to interest expense	9.942	7.441
SI	Short interest, number of shares shorted as a percentage of total shares outstanding	4.139	2.145

Table 2. Univariate Sample Comparison

This table reports the mean values of the variables in the sample across various firm characteristics. Variable definitions are as defined by Table 1. Firms are separated depending on whether their current month's short interest (or change in short interest over the past three months) is above or below the median of the sample. The sample consists of 213,754 coupon-paying, plain-vanilla corporate bonds of nonfinancial firms. The data is obtained from the Mergent's FISD database. The sample period covers January 1994 through December 2019. The data for term structure is from Board Governors of Federal Reserve. All accounting data are from the annual COMPUSTAT.

	Lagged One Month Short Interest				Lagged Three Months Short Interest			
Variable	Low Short Interest (N = 106,877)	High Short Interest (N = 106,877)	Mean Difference	Mean Comparison p-value	Low Short Interest (N = 106,843)	High Short Interest (N = 106,842)	Mean Difference	Mean Comparison p-value
CSPRD	1.469	2.267	0.797	0.0001	1.473	2.264	0.791	0.0001
CRD	8.843	10.601	1.758	0.0001	8.844	10.603	1.759	0.0001
ZSCORE†	1.593	1.524	-0.068	0.0001	1.596	1.522	-0.074	0.0001
LEVEL	1.354	1.362	0.008	0.0001	1.357	1.358	0.001	0.0001
SLOPE	1.520	1.511	-0.009	0.0001	1.515	1.516	0.000	0.0001
EUROD	0.392	0.399	0.007	0.0001	0.391	0.400	0.009	0.0001
AGE	3.922	4.167	0.246	0.5629	3.922	4.167	0.245	0.6668
MAT	10.604	9.241	-1.363	0.0001	10.592	9.250	-1.342	0.0001
LIQ	0.014	0.013	-0.001	0.0001	0.014	0.013	0.000	0.0001
RETVOL	0.070	0.086	0.016	0.0001	0.070	0.086	0.016	0.0001
EARNVOL	0.150	0.146	-0.004	0.0002	0.151	0.145	-0.006	0.0002
TD2CAP	0.774	1.226	0.453	0.0001	0.779	1.221	0.442	0.0001
LTDB	0.302	0.332	0.029	0.0001	0.302	0.332	0.030	0.0001
QUIK	0.150	0.134	-0.016	0.0001	0.150	0.134	-0.016	0.0001
ROA	1.158	1.620	0.463	0.0001	1.158	1.621	0.463	0.0001
INTCOV	11.546	8.342	-3.204	0.0001	11.537	8.346	-3.191	0.0001
SI	1.440	6.832	5.393	0.0001	1.552	6.728	5.176	0.0001

are largely confirmed within various subsamples of the panel.

As noted, our main hypothesis is that if short sellers have any ability to detect deteriorating fundamentals, high short-selling activity could affect the pricing of corporate bonds and predict higher credit spreads. To directly address this issue, we estimate the empirical model as represented by Equation (1). Consistent with our main hypothesis, we find that subsequent credit spreads do increase with short interest, as displayed in Table 3. The regression coefficients corresponding to one-month and three-month lagged short interest are positive and statistically significant at better than 1%. A one percentage rise in one-month (three-month) lagged short interest corresponds to 2.098 (1.921) basis points wider spreads. All the regressions use robust (i.e., the White, 1980, heteroskedasticity adjusted), with standard errors corrected for firm-level clustering.

The coefficient on one-month lagged short interest, depending on specifications (i.e., panel, Newey-West, Fama-McBeth, and cross-sectional regressions), is respectively 2.098, 2.937, 1.035, and, 2.756 (statistically significant at the 1% level). The coefficient on three-month lagged short interest, depending on specifications (i.e., panel, Newey-West, FamaMcBeth, and cross-sectional regressions), is respectively 1.921, 2.285, 1.237, and, 3.524 (statistically significant at the 1% level). These findings support our prediction that investors discount bond prices in response to higher equity short selling. Therefore, the results are consistent with the idea that short-selling activity in the equity market is informative for the corporate bond market too.

Robustness Analyses

Short Sale Effects across Different Firm Characteristics

A main concern for this analysis is whether the effect of the short selling is confounded by the inherent nonlinearity of the credit spreads and whether short interest could be more informative for different sets of firms. Extant structural models suggest that credit spreads are nonlinearly related to firms' 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) finds that credit spreads and other measures like firm size are also linked in a distinctly nonlinear fashion. To control for these nonlinearities, we follow the convention of extant literature (e.g., Campbell & Taksler, 2003; Chen et al., 2007; Collin-Dufresne et al., 2001; Nejadmalayeri & Singh, 2012; Nejadmalayeri et al., 2013) and estimate the baseline regression model separately for firms sorted on credit rating, firm size, and leverage. We combine our firms into three general credit categories: AAA to AA- rated firms, A+ to BBB- rated firms, and the rest. We use the COMPUSTAT 33% and 67% cut-offs of firm size and leverage to divide the sample. To further measure the informational relevancy of short interest, we also sort our sample based on variables that capture informational asymmetry: return volatility and insider trading (i.e., changes in chief executive's stocks and option holdings). We divide our sample tertiles according to return volatility. We also define three categories of insider trading: purchase of stocks or options, sale of stocks or options up to 50% of the prior year's holdings, and the rest. We then run baseline regressions for the aforementioned subsamples.

The results are reported in Table 4 and suggest that the positive relationship between short interest and credit spread is robust. However, important regularities exist in regard to how short interest affects credit spreads. The coefficient estimates of short interest are only statistically significantly positive for low-rating firms, suggesting that bond investors worry the most when they see high short-selling activity for low-rated firms. The coefficient estimates for the one-month (three-month) lagged short interest are 1.332 and 2.413 (1.166 and 2.187) for mid- and low-rated bonds, respectively (statistically significant at better than the 1% level). The impact of short interest on credit spread is increasing with firm size. The coefficient estimates for the one-month (three-month) lagged short interest are 3.055, 1.780, and 1.067 (3.068, 1.474, and 0.841) for small, mid-sized, and large firms, respectively (statistically significant at better than the 1% level except for large firms). As in prior studies based on equity prices, we find greater impact of short interest among small firms.

Table 4 shows that the impact of short interest on credit spread is nonlinear with leverage. The coefficient estimates for the one-month (three-month) lagged short interest are 1.445, 2.515, and 2.472 (1.388, 2.335, and 2.080) for low-, medium-, and high-leverage firms, respectively (statistically significant at better than the 1% level). The impact of short interest on the credit spread is increasing with return volatility. The coefficient estimates for the one-month (three-month) lagged short interest are 0.794, 1.621, and 2.867 (0.624, 1.692, and 2.470) for low-, medium-, and high-volatility firms, respectively (statistically significant at better than the 1% level).

Lastly, Table 4 shows that the impact of short interest on credit spread is greater for firms where executives sell their options heavily. The coefficient estimates for the

Table 3. Corporate Credit Spreads and Short Interest

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. LAG1SI (LAG3SI) is the level of short interest measured as one month (three months) before credit spread is observed. 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. For brevity, the coefficients on year, industry, and firm dummy variables are not reported. Robust (heteroskedasticity, autocorrelation, and firm-clustering corrected) t-statistics are reported in parentheses. Coefficients that are statistically different from zero are marked at 1%, 5%, and 10% levels with ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel Regression with Fixed Effects	**Panel with Newey-West Standard Errors**	**Fama-McBeth Regression**	**Cross-Sectional Regression**	**Panel Regression with Fixed Effects**	**Panel with Newey-West Standard Errors**	**Fama-McBeth Regression**	**Cross-Sectional Regression**
LAG1SI	**2.098*****	**2.397*****	**1.035****	**2.756*****				
	(5.680)	**(25.210)**	**(2.450)**	**(6.800)**				
LAG3SI					**1.921*****	**2.285*****	**1.237*****	**3.524*****
					(5.090)	**(24.330)**	**(6.020)**	**(8.510)**
CRD	0.029***	0.119***	0.132***	0.055***	0.029***	0.119***	0.131***	0.054***
	(3.490)	(36.540)	(16.280)	(7.050)	(3.540)	(36.550)	(21.400)	(6.920)
ZSCORE†	-0.195***	-0.042***	0.000	-0.136***	-0.194***	-0.041***	0.003	-0.137***
	(-3.360)	(-6.680)	(0.050)	(-6.760)	(-3.340)	(-6.590)	(0.280)	(-6.830)
LEVEL	-0.432***	-0.145***	-0.438	-0.121***	-0.431***	-0.145***	-0.444	-0.113***
	(-16.890)	(-35.920)	(-0.930)	(-5.000)	(-16.990)	(-35.930)	(-0.940)	(-4.710)
SLOPE	-0.446***	-0.024**	-0.153	0.162**	-0.449***	-0.025***	-0.313	0.167***
	(-18.010)	(-2.490)	(-0.550)	(2.510)	(-18.070)	(-2.620)	(-1.510)	(2.590)
EUROD	1.073***	1.356***	0.467	1.164***	1.070***	1.356***	0.389	1.146***
	(25.890)	(94.100)	(0.980)	(8.220)	(25.890)	(94.320)	(0.850)	(8.150)
LogAGE	0.213***	0.108***	0.076***	0.218***	0.213***	0.109***	0.076***	0.213***
	(21.070)	(31.230)	(10.450)	(5.880)	(21.130)	(31.330)	(10.430)	(5.770)
LogMAT	0.216***	0.117***	0.012	0.072***	0.216***	0.116***	0.009	0.076***
	(20.610)	(36.450)	(0.740)	(2.910)	(20.590)	(36.270)	(0.570)	(3.090)
LIQ	-0.318	-6.007***	-6.459***	-19.819***	-0.372	-6.059***	-6.488***	-18.058***
	(-0.750)	(-16.310)	(-11.630)	(-3.710)	(-0.880)	(-16.460)	(-11.910)	(-3.400)
RETVOL	7.216***	14.541***	10.959***	14.343***	7.217***	14.550***	11.206***	14.159***
	(13.800)	(55.300)	(20.300)	(28.570)	(13.680)	(55.370)	(20.180)	(28.280)
EARNVOL	0.025	0.046***	0.779**	-0.070	0.024	0.045***	0.725**	-0.069
	(0.870)	(5.120)	(2.250)	(-0.970)	(0.840)	(5.030)	(2.050)	(-0.940)
TD2CAP	0.296***	0.199***	0.131***	0.354***	0.294***	0.198***	0.130***	0.352***
	(6.630)	(21.860)	(10.760)	(23.700)	(6.520)	(21.790)	(11.510)	(23.630)
LTDB	0.317	1.081***	0.778***	1.679***	0.319	1.082***	0.734***	1.685***
	(1.530)	(29.100)	(7.670)	(10.340)	(1.530)	(29.130)	(6.370)	(10.420)
ROA	-1.656***	-1.518***	-0.788**	-2.439***	-1.689***	-1.531***	-0.772**	-2.384***
	(-3.830)	(-19.690)	(-2.320)	(-6.540)	(-3.940)	(-19.880)	(-2.560)	(-6.420)
QUIK	0.009	-0.016***	-0.011	-0.022**	0.009	-0.016***	-0.007	-0.025**
	(0.670)	(-6.380)	(-0.870)	(-2.030)	(0.660)	(-6.250)	(-0.600)	(-2.290)
INTD1	-0.031***	-0.029***	-0.073***	-0.082***	-0.031***	-0.029***	-0.073***	-0.085***
	(-3.820)	(-14.510)	(-5.800)	(-3.830)	(-3.840)	(-14.440)	(-6.690)	(-4.010)
INTD2	0.020**	0.004	0.053***	-0.039	0.020**	0.004	0.049***	-0.033
	(2.300)	(1.490)	(2.810)	(-1.290)	(2.330)	(1.510)	(2.910)	(-1.090)
INTD3	0.002	0.009***	-0.005	0.043**	0.002	0.009***	-0.006	0.041**
	(0.460)	(6.840)	(-0.720)	(2.300)	(0.460)	(6.850)	(-0.780)	(2.210)
INTD4	0.000	0.002***	-0.005	0.000	0.000	0.002***	-0.004	0.001
	(0.050)	(3.000)	(-0.820)	(0.020)	(0.030)	(2.880)	(-0.620)	(0.080)
Constant	2.174***	-1.228***	0.142	-0.409**	2.173***	-1.226***	0.394	-0.449**
	(9.000)	(-33.410)	(0.220)	(-2.150)	(8.940)	(-33.300)	(0.720)	(-2.370)
Year dummies	Yes	—	—	—	Yes	—	—	—
Industry dummies	Yes	—	—	—	Yes	—	—	—
Firm dummy	Yes	—	—	—	Yes	—	—	—
N.Obs.	213,754	213,754	213,754	5,483	213,685	213,685	213,685	5,479
Adj. R^2	0.7243	0.6913	0.5775	0.4923	0.7239	0.6892	0.5773	0.4953

DOI: *https://doi.org/10.35692/07183992.13.2.5*

Table 4. Credit Spreads and Short Interest across Subsamples

This table reports the results of the robustness panel regression models of the credit spread using various measures of short sale (short interest) across different categories. A firm is denoted as low, medium, or high leverage if the ratio of its long-term debt to total assets is, respectively, in the bottom, middle, or top thirds of the COMPUSTAT universe. A firm is denoted as small-cap, mid-cap, or 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, or top thirds of the COMPUSTAT universe. A firm is denoted as low, medium, or high return volatility if the 12-month rolling return standard deviation is, respectively, in the bottom, middle, or top thirds of the sample. Firms are also separated based on executive stock and option trading into three categories of increase in executive stock or option holdings, moderate (less than 50%) and large (more than 50%) decrease of stock and option holdings. For brevity, coefficients on control variables are not reported. Robust (heteroskedasticity, autocorrelation, and firm-clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero are marked at 1%, 5%, and 10% levels with ***, **, and *, respectively.

	AAA – AA Rated	A – BBB Rated	BB – C Rated	Small-Cap Firms	Mid-Cap Firms	Large-Cap Firms	Low Leverage	Medium Leverage	High Leverage
LAG1SI	2.026*	1.332***	2.413***	3.055***	1.780***	1.067*	1.445**	2.515***	2.472***
	(1.930)	(4.560)	(3.200)	(4.190)	(3.190)	(1.910)	(2.320)	(3.850)	(4.720)
N.Obs.	20,630	163,624	28,086	50,290	79,221	84,243	80,733	76,714	56,307
Adj. R^2	0.8947	0.6818	0.6567	0.7513	0.6946	0.6805	0.7136	0.7192	0.7660
LAG3SI	2.110	1.166***	2.187***	3.068***	1.474***	0.841	1.388**	2.335***	2.080***
	(1.640)	(3.980)	(2.880)	(4.150)	(2.780)	(1.580)	(2.310)	(3.430)	(3.530)
N.Obs.	20,626	163,570	28,075	50,274	79,200	84,211	80,714	76,674	56,297
Adj. R^2	0.8949	0.6813	0.6560	0.7512	0.6940	0.6801	0.7136	0.7184	0.7656
	Low Return Volatility	**Medium Return Volatility**	**High Return Volatility**	**Executive Stocks Increase**	**Executive Stocks Decrease < 50%**	**Executive Stocks Decrease ≥ 50%**	**Executive Options Increase**	**Executive Options Decrease < 50%**	**Executive Options Decrease ≥ 50%**
LAG1SI	0.794***	1.621***	2.867***	3.248***	1.595***	1.685*	2.224***	1.387**	3.806***
	(3.220)	(4.230)	(4.530)	(5.080)	(4.490)	(1.910)	(5.610)	(2.310)	(4.470)
N.Obs.	82,716	78,148	52,890	73,090	129,305	11,359	124,945	74,461	14,348
Adj. RSQ.	0.7079	0.7117	0.7204	0.7567	0.7302	0.7821	0.7496	0.7359	0.7991
LAG3SI	0.624***	1.692***	2.470***	3.132***	1.396***	1.498*	2.022***	1.212**	3.395***
	(2.820)	(4.320)	(3.830)	(5.030)	(3.530)	(1.730)	(5.440)	(2.010)	(4.510)
N.Obs.	82,713	78,099	52,873	73,069	129,263	11,353	124,891	74,449	14,345
Adj. R^2	0.7074	0.7116	0.7198	0.7565	0.7297	0.7820	0.7492	0.7357	0.7972

one-month (three-month) lagged short interest are 2.224, 1.387, and 3.806 (2.022, 1.212, and 3.395) for option purchasers, moderate option sellers, and heavy option sellers, respectively (statistically significant at better than the 1% level). However, we find that credit spread is non-linearly linked with executives' stock selling. The coefficient estimates for the one-month (three-month) lagged short interest are 3.248, 1.595, and 1.684 (3.131, 1.396, and 1.498) for stock purchasers, moderate stock sellers, and heavy stock sellers, respectively (statistically significant at better than the 1% level). As Coles, Daniel, and Naveen (2006) show, greater high-power incentive compensation motivates excessive risk-taking. When executives heavily sell highly levered parts of their wealth (options), a rise in short selling sends a strong negative signal about the firm's prospects. But heavy purchasing by executives can also mean greater incentives for future excessive risk taking.

Impact of Policy Uncertainty

A concern for our analysis is whether the effect of the short selling is confounded by the overall uncertainty. Following Javadi, Nejadmalayeri and Krehbiel (2018), we use a host of policy uncertainty indexes (à la Baker, Bloom, & Davis, 2016) to examine how various dimensions of uncertainty (i.e., news, economics, monetary, taxation, fiscal, government, regulations, and trade) affect our earlier results. As is shown in Table 4, while all eight dimensions have significant impact on credit spread, their inclusion does not materially impact the extenuating impact of lagged short interest on credit spreads. Irrespective of specification, the coefficient estimate on

Table 5. Robustness Analysis: Impact of Policy Uncertainty

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. All policy uncertainty indexes are from www.policyuncertainty.com and are based on the seminal work of Baker et al. (2016). LAG1SI (LAG3SI) is the level of short interest measured as one month (three months) before credit spread is observed. LogAGE and LogMAT are natural logarithms of a 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. For brevity, the coefficients on year, industry, and firm dummy variables are not reported. Robust (heteroskedasticity, autocorrelation, and firm-clustering corrected) *t*-statistics are reported in parentheses. Coefficients that are statistically different from zero are marked at 1%, 5%, and 10% levels with ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PUI News	**PUI Economics**	**PUI Monetary**	**PUI Taxation**	**PUI Fiscal**	**PUI Government**	**PUI Regulations**	**PUI Trade**
LAG1SI	**2.096*****	**2.096*****	**2.096*****	**2.101*****	**2.101*****	**2.100*****	**2.107*****	**2.107*****
	(5.630)	**(5.640)**	**(5.620)**	**(5.640)**	**(5.640)**	**(5.640)**	**(5.650)**	**(5.670)**
PUI	0.129***	0.238***	0.078***	0.079***	0.081***	0.038***	0.073***	0.059***
	(17.270)	(16.820)	(9.580)	(12.060)	(12.740)	(14.010)	(10.920)	(16.040)
N.Obs.	213,754	213,754	213,754	213,754	213,754	213,754	213,754	213,754
Adj. R^2	0.7241	0.7250	0.7237	0.7239	0.7240	0.7238	0.7237	0.7244

one-month lagged short interest is approximately 2.1 (significant at better than 1% level).

Conclusion

We examine the relationship between short-selling activity in the equity market and corporate bond prices. Extant research posits that short sellers are informed traders and increased short selling reflects information about deteriorating corporate fundamentals. Given the liquidity of equity markets, the adverse information of large short interest can become an invaluable source of information for markets of corporate debt claims where lack of liquidity severely limits the extent to which corporate bond trading can channel information. We provide evidence that the level of short interest is indeed informative regarding corporate bond prices too, indicating that short selling contains pertinent, timely, value-relevant information content.

Using a battery of regression analyses, we find evidence that otherwise similar corporate bonds will carry significantly larger credit spreads one and three months ahead when current short selling is higher. Our findings are consistent with the idea that rising short sales indicate the firm will face financial difficulties and therefore bondholders sell these bonds in anticipation of the future adverse outcomes. The relationship between short interest and subsequent credit spreads is more pronounced among firms with lower credit ratings, higher leverage, high volatility, and heavier insider selling, suggesting that bond investors attach more value to the level of short selling for riskier firms.

Our results point to the critical informativeness of equity short selling for the valuation of corporate bonds. Possible extensions of our work lie with both capital market implications and corporate finance applications. For instance, since shorting corporate bonds are prohibitively expensive, do credit default swap prices better reflect adverse information in the equity short selling? In a horse-race market price information who wins: credit default swaps, corporate bonds, or equity short sellers? Relatedly, does higher short selling make future borrowing harder? Do firms with large short interest face a credit crunch?

References

Acharya, V., & Carpenter, J. N. (2002). Corporate bond valuation and hedging with stochastic interest rates and endogenous bankruptcy. *Review of Financial Studies, 15*(5), 1355-1383.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*, 589-609.

Asquith, P., Pathak, P.A., & Ritter, J. R. (2005). Short interest, institutional ownership, and stock returns. *Journal of Financial Economics, 78*(2), 243-276.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593-1636.

Blume, M. E., Lim, F., & MacKinlay, C. (1998). The declining credit quality of U. S. corporate debt: Myth or reality. *Journal of Finance, 53*(4), 1389-1413.

Boehme, R.D., Danielsen, B., & Sorescu, S. (2006). Short sale constraints, differences of opinion, and overvaluation. *Journal of Financial and Quantitative Analysis, 41*(2), 455-487.

Boehmer, E., Jones, C., & Zhang, X. (2008). Which shorts are informed? *Journal of Finance, 63*(2), 491-527.

Callen, J., Livnat, J., & Segal, D. (2009). The impact of earnings on the pricing of credit default swaps. *The Accounting Review, 84*(5), 1363-1394.

Campbell, J. (1991). A variance decomposition for stock returns. *The Economic Journal, 101*(405), 157-179.

Campbell, J., & Shiller, R. (1988a). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies, 1*(3), 195-228.

Campbell, J., & Shiller, R. (1988b). Stock prices, earnings, and expected dividends. *Journal of Finance, 43*(3), 661-676.

Campbell, J., & Taksler, G. (2003). Equity volatility and corporate bond yields. *Journal of Finance, 58*(6), 2321-2349.

Chen, L., Lesmond, D., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *Journal of Finance, 62*(1), 119-149.

Christophe, S., Ferri, M., & Angel, J. (2004). Short-selling prior to earnings announcements. *Journal of Finance, 59*(4), 1845-1875.

Christophe, S., Ferri, M., & Hsieh, J. (2010). Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics, 95*(1), 85-106.

Cohen, L., Diether, K., & Malloy, C. (2007). Supply and demand shifts in the shorting market. *Journal of Finance, 62*(5), 2061-2096.

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial risk-taking. *Journal of Financial Economics, 79*(2), 431-468.

Collin-Dufresne, P., Goldstein, R., & Martin, S. (2001). The determinants of credit spread changes. *Journal of Finance, 56*(6), 2177-2207.

Covitz, D., & Downing, C. (2007). Liquidity or credit risk? The determinants of very short-term corporate yield spreads. *Journal of Finance, 62*(5), 2303-2328.

Dechow, P., Hutton, A., Meulbroek, L., & Sloan, R. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics, 61*(1), 77-106.

Desai, H., Krishnamurthy, S., & Venkataraman, K. (2006). Do short sellers target firms with poor earnings quality? Evidence from earnings restatements. *Review of Accounting Studies, 11*(1), 71-90.

Desai, H., Ramesh, K., Thiagarajan, R., & Balacahandran, B. (2002). An investigation of the informational role of short interest in the NASDAQ market. *Journal of Finance, 57*(5), 2263-2287.

Diamond, D., & Verrecchia, R. (1987). Constraints on short selling and asset price adjustment to private information. *Journal of Financial Economics, 18*(2), 277-311.

Diether, K., Lee, K., & Werner, I. (2009). Short-sale strategies and return predictability. *Review of Financial Studies, 22*(2), 575-607.

Duffee, G. (1998). The relation between treasury yields and corporate bond yields spreads. *Journal of Finance, 53*(6), 2225-2241.

Elton, E., Gruber, M., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance, 56*(1), 247-277.

Eom, Y., Helwege, J., & Huang, J. (2004). Structural models of corporate bond pricing: An empirical analysis. *Review of Financial Studies, 17*(2), 499-544.

Gebhardt, W., Hvidkjaer, S., & Swaminathan, B. (2005). The cross-section of expected corporate bond returns: Betas or characteristics? *Journal of Financial Economics, 75*(1), 85-114.

Güntay, L., & Hackbarth, D. (2010). Corporate bond credit spreads and forecast dispersion. *Journal of Banking and Finance, 34*(10), 2328-2345.

Helwege, J., & Turner, C. (1999). The slope of the yield curve for speculative-grade issuers. *Journal of Finance, 54*(5), 1869-1884.

Henry, T., Kisgen, D., & Wu, J. (2010). *Do equity short sellers anticipate bond rating downgrades?* (Working Paper). University of Georgia, Boston College.

Hirshleifer, D., Teoh, S., & Yu, J. J. (2011). Short arbitrage, return asymmetry, and the accrual anomaly. *Review of Financial Studies, 24*(7), 2429-2461.

Javadi, S., Nejadmalayeri, A., & Krehbiel, T. (2018). Do FOMC actions speak loudly? Evidence from corporate bond credit spreads. *Review of Finance, 22*(5), 1877-1909.

Jones, C., & Lamont, O. (2002). Short-sale constraints and stock returns. *Journal of Financial Economics, 66*(2-3), 207-239.

Ju, N., & Ou-Yang, H. (2006). Capital structure, debt maturity, and stochastic interest rates. *Journal of Business, 79*(5), 2469-2502.

Karpoff, J., & Lou, X. (2010). Short sellers and financial misconduct. *Journal of Finance, 65*(5), 1879-1913.

Leland, H. (1994). Corporate debt value, bond covenants, and optimal capital structure. *Journal of Finance, 49*(4), 1213-1252.

Litterman, R., & Scheinkman, J. (1991). Common factors affecting bond returns. *Journal of Fixed Income, 1*(1), 1-18.

Longstaff, F., & Schwartz, E. (1995). A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance, 50*(3), 789-819.

Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance, 29*(2), 449-470.

Miller, E. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance, 32*(4), 1151-1168.

Nejadmalayeri, A., & Singh, M. (2012). Corporate taxes, strategic default, and the cost of debt. *Journal of Banking and Finance, 36*(11), 2900-2916.

Nejadmalayeri, A., Singh, M., & Mathur, I. (2013). Product market advertising and corporate bonds. *Journal of Corporate Finance, 19*, 79-94.

Perraudin, W., & Taylor, A. (2004). On the consistency of ratings and bond market yields. *Journal of Banking and Finance, 28*(11), 2769-2788.

Warga, A. (1992). Bond returns, liquidity, and missing data. *Journal of Financial and Quantitative Analysis, 27*(4), 605-617.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817-838.