The Role of Social Media in the Corporate Bond Market: Evidence from Twitter

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ABSTRACT:
Prior studies document the role social media information plays in the stock market as well as the important dissimilarities between the bond and stock markets. Bridging these two literatures, we examine the role of social media information in the corporate bond market. Analyzing a broad sample of messages by Twitter individual users, posted just prior to earnings announcements, containing bond, credit risk, and fundamental information, we find that aggregate Twitter opinion (*OPI*) predicts upcoming announcement bond returns and changes in CDS spreads, and is associated with future changes in bond yield spreads and credit ratings, thereby providing economically important information to the bond market. This interpretation is bolstered by results from a variety of cross-sectional analyses. Finally, we document an association between *OPI* and future changes in default risk, which casts light on the nature of the Twitter information underlying our findings. Overall, our findings demonstrate that Twitter appears to disseminate potentially economically important information to even the presumably sophisticated bond and CDS investors, as well as information intermediaries.

Keywords: Twitter, social media, credit risk, default risk, bankruptcy risk, earnings, CDS, bond yield, bond returns.

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I. INTRODUCTION

The rise of the Internet has led to an explosion of new sources of information that are easily accessible to the public at large and to capital market participants in particular, which, in turn, brought together investors around the globe, enabling an open exchange of information and ideas. Undoubtedly, the biggest revolution in the dissemination of financial information on the Internet has been the advent of social media platforms, such as Twitter and Reddit, that allow users to post instantaneously to a wide audience their views about firms and their prospects.

Academic research in both finance and accounting focuses on the usefulness of information from online sources and social media platforms for stock market participants. Hirschey et al. (2000) find that investment reports on bulletin boards such as Motley Fool predict stock returns. Chen et al. (2014) demonstrate that information in reports on the SeekingAlpha portal helps predict earnings and long-window stock returns following their posting. Jame et al. (2016) find that crowdsourced (Estimize) forecasts are a useful supplementary source of information in capital markets, and Jung et al. (2018) show that corporate adoption of social media (especially Twitter) is increasing rapidly. Finally, Bartov et al. (2018) show that the aggregate opinion from individual Twitter messages successfully predicts a firm's forthcoming quarterly earnings and announcement stock returns. Collectively, these papers highlight the informational value of online sources and social media platforms for equity investors.

In assessing the usefulness of social media information, both prior research and the investment community—which has been using predictive information in social media to inform investment strategies (*Wall Street Journal* 2014)—focus on the stock market, paying little attention to an important segment of the financial markets, the bond markets.[1] However, there are

[1] According to the Securities Industry and Financial Markets Association (SIFMA), at the end of 2017, the total amount of debt outstanding in U.S. bond markets exceeds \$40.7 trillion, of which more than \$9 trillion is corporate

considerable differences between the nature of the participants in the stock and corporate bond markets and the information they require, as well as between the structure and trading mechanism underlying the two markets.

First, in contrast to the stock market, where retail stock investors actively trade in exchanges, corporate bond investors are almost exclusively institutions, such as broker-dealers and large financial institutions (e.g., banks, hedge funds, insurance companies), which, unlike retail investors, are generally sophisticated market participants. Second, parties with access to private information rate corporate bonds. Clearly, these ratings provide potentially relevant information to bond investors that can serve, for example, as an independent check on the accuracy and reliability of analysts' bond recommendations. Third, the nature of information required by stock investors—primarily related to earnings and earnings growth (e.g., Ohlson and Juettner-Nauroth 2005)—differs substantially from that required by bond investors, predominantly pertaining to credit risk and particularly default risk (see, e.g., Fama and French 1993; De Franco et al. 2009).[2] Fourth, in contrast to the stock market, trading in the corporate bond market is primarily in decentralized over-the-counter (OTC) markets, which are less regulated and transparent than stock exchanges.[3] In summary, prior studies highlight major dissimilarities between the stock and corporate bond markets and conclude that the dissimilarities may lead to systematic differences in the distribution of bond-related public information and the bond market reaction to this information.

This suggests that the extent to which social media platforms disseminate *relevant*

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debt, compared to the U.S. stock market capitalization of $32.1 trillion (https://www.sifma.org/wp-content/uploads/2018/09/US-Capital-Markets-Deck-2018-09-06-SIFMA.pdf, accessed March 15, 2022).

[2] Default risk arises when a bond issuer is unable to make timely interest or principal payments. Credit risk includes default risk, downgrade risk (risk of a decrease in credit rating), and credit spread risk (risk of credit spreads widening).

[3] Transactions in financial markets are either organized in exchanges, such as the New York Stock Exchange or Nasdaq, or occur OTC. Unlike exchange trades, OTC trades are executed directly between two parties without a central exchange or a broker. Consequently, a trade can be executed between two participants in OTC markets without others being aware of the price of the completed transaction. As OTC markets are not subject to the regulations of major exchanges (e.g., timely information disclosure), they are less transparent.

information to bond market participants is an open and interesting empirical question. We thus study the following research question: does social media provide relevant and economically important information to the corporate bond market?

To study this question, we analyze the aggregate opinion from individual messages posted on Twitter just prior to a firm's quarterly earnings release (henceforth, aggregate Twitter opinion or *OPI*). We estimate *OPI* by first analyzing the content of each tweet using textual analysis, and then aggregating the textual-analysis results across all tweets by firm-quarter. In deriving *OPI*, we employ commonly used dictionaries that identify the negative and positive words in each individual tweet. We restrict our sample to tweets mentioning words and phrases related to bond, credit risk, fundamentals, and/or securities trading. We measure *OPI* in a short period prior to quarterly earnings announcements because Twitter users pay special attention to companies' performance and value just prior to their earnings releases, as evidenced by a spike in Twitter activity during that period (see, e.g., Ranco et al. 2015; Curtis et al. 2016; Gabrovšek et al. 2017). We choose Twitter as our data source because, among other reasons, Twitter information is rich and reflects numerous and widely diverse opinions, suggesting it may cover many aspects of firm attributes of interest not only to equity investors, but also to bond investors. However, we acknowledge that Twitter information may not be relevant to bond investors as the discussion on Twitter may primarily pertain to stocks' prospects and stock prices, not bonds. Further, while Bartov et al. (2018) find that Twitter is informative to the stock market, Twitter's individual users may be generally unsophisticated and thus provide little incremental information to the more complex and less transparent corporate bond market.

We begin our empirical investigation by testing the ability of *OPI* to predict bond returns and changes in credit default swap (CDS) contracts' spreads around the upcoming quarterly earnings announcements.[4] We focus on a short window around earnings announcements because

[4] The "spread" of a CDS contract is an annual fixed premium paid by the protection buyer to the protection seller over the length of the contract, quoted in basis points per annum of the contract's notional amount.

prior research shows that bond-trading volume increases sharply around earnings announcements (Easton et al. 2009; Callen et al. 2009; Ronen and Zhou 2013; Even-Tov 2017). A significant association between *OPI* and announcement bond returns/changes in CDS spreads would demonstrate that *OPI* provides economically important, forward-looking valuation-relevant information to the bond market. To complement these short-window tests, we also examine the association between *OPI* and changes in bond yield spreads—where the spread is the difference between the yield to maturity of a traded bond and the yield to maturity of a Treasury security with a corresponding duration—over two alternative long windows, [q-1; q+1] and [q-1; q+3], where q is the quarter where *OPI* is measured.

We find that *OPI* is significantly positively associated with bond returns and significantly negatively associated with changes in CDS spreads around quarterly earnings announcements. Our results control for earnings surprises and announcement stock returns, suggesting that the bond market reaction is incremental to, and not merely a reflection of the previously documented association between aggregate Twitter opinion and future earnings and stock returns. In addition, Easton et al. (2009) show that bond prices are more sensitive to bad earnings news than good earnings news, consistent with the nonlinear payoff structure of bonds. Using analyst earnings forecast errors to measure the nature of the news, we confirm this finding in our setting, by showing that the association between *OPI* and announcement bond returns (changes in CDS spreads) is more positive (more negative) for bad news compared to good news. Cross-sectional tests indicate that the association between *OPI* and announcement bond returns/changes in CDS spreads is stronger for tweets containing information directly related to bonds and credit risk and when information uncertainty is high. Further, we corroborate these findings in long-windows tests using changes in bond yield spreads.

Next, we investigate whether Twitter information is associated with the information used by intermediaries, specifically credit rating agencies. To that end, we test whether *OPI* is associated with a future credit rating change, measured by the likelihood of a credit rating downgrade or upgrade. Consistent with the nonlinear payoff structure of bonds, we find that *OPI* is significantly negatively associated with the probability of a future credit rating downgrade, but insignificantly related to the probability of a future upgrade. These results suggest that aggregate Twitter opinion reflects the information used by credit rating agencies, and hence further supports that Twitter may be a potentially relevant source of information.

Finally, we assess the nature of the Twitter information underlying our results. Clearly, for Twitter information to be useful, it must be forward looking and valuation relevant. As the prediction of default is of a prime interest to bond investors (Hillegeist et al. 2004; Beaver et al. 2011; Akins 2018), we examine whether *OPI* is associated with future changes in default risk. We measure changes in default risk as changes in implied default probability from three popular models: the Altman Z-Score, the Ohlson O-Score, and the Black-Scholes-Merton models. We find that *OPI* is strongly negatively associated with future changes in implied default probability for all three measures. Further, this association is stronger for speculative-grade bonds, confirming findings in prior studies that speculative-grade bond prices show a greater sensitivity to news compared to investment-grade bonds (Easton et al. 2009; Gkougkousi 2014; Even-Tov 2017). Likewise, this association is stronger for firms with greater information uncertainty, where Twitter information is more likely to be incrementally meaningful.

Overall, our findings suggest that aggregate Twitter opinion appears to disseminate potentially relevant and economically important information, not only for stock market investors as documented by Bartov et al. (2018), but also for corporate bond market investors and information intermediaries. We contribute to the literatures on the role of social media in capital markets and the role of earnings and financial disclosures in the corporate bond market. These two literatures have demonstrated, respectively, that Twitter information helps predict quarterly earnings and announcement stock-price changes (Bartov et al. 2018), and that the nonlinear payoff structure of bonds has important implications for the reaction of bond prices to earnings news (Easton et al. 2009). We contribute to these literatures by providing novel evidence that social media conveys economically important information to even the presumably sophisticated investors who dominate the corporate bond market, an important financial market that differs significantly from the stock market, as well as to credit rating agencies. Our findings may thus inform bond and CDS investors, bond analysts, and credit rating agencies in their investing and credit analysis.

The remainder of the paper is organized as follows. Section II presents a review of the relevant prior literature. Section III develops our research question and outlines the research design. Section IV describes the data, and Section V presents the empirical results. The final section, Section VI, summarizes our main findings and conclusions.

II. REVIEW OF RELATED LITERATURE

Our study relates to the literatures on the role of social media in capital markets, the differences between stock and corporate bond markets, and the role of financial disclosures in the corporate bond market.

The Role of Social Media in Capital Markets

There is a growing literature in finance and accounting on the role of social media in capital markets. Hirschey et al. (2000) find that investment reports on bulletin boards such as Motley Fool predict stock returns. Chen et al. (2014) investigate the extent to which investor opinions predict future stock returns and earnings surprises, by conducting textual analysis of articles posted on the Seeking Alpha portal as well as readers' comments in response to these articles. They find that the views expressed in both articles and commentaries predict future long-window stock returns and earnings surprises. Jame et al. (2016) find that crowdsourced earnings forecasts on the Estimize platform are a useful supplementary source of information to predict earnings. Jung et al. (2018) show that corporate adoption of social media, such as Facebook and especially Twitter, is increasing rapidly. Curtis et al. (2016) document that high levels of social media activity (on Twitter and StockTwits) are associated with greater stock market reaction to earnings news. Finally, more closely related to our study, Bartov et al. (2018), find that aggregate Twitter opinion successfully predicts a firm's forthcoming quarterly earnings and announcement stock returns.

However, this research focuses solely on the stock market, paying little attention to the role of social media in the corporate bond market. Still, as discussed below, ample empirical evidence indicates substantial differences between the stock and corporate bond markets. Whether the findings of the research focusing on the stock market can be extrapolated to the corporate bond market is, thus, an open empirical question.

Differences between Stock and Corporate Bond Markets

Fama and French (1993) find that the excess market return factor and two mimicking returns for the size and book-to-market factors, which together explain the cross-sectional variation in stock returns, have generally little explanatory power for the variation in returns of corporate bonds once two mimicking portfolios for a term premium and a default premium are introduced to the regression. Ohlson and Juettner-Nauroth (2005) show that earnings and short- and long-term earnings growth are important for equity valuation, and Datta and Dhillon (1993) observe that if earnings news indicates that the variance (as opposed to mean) of expected cash flows changes, stock and bond returns are expected to adjust in opposite directions.

De Franco et al. (2009) document differences between the bond and stock markets including that the distribution of bond analysts' recommendations of buy, hold, and sell is less positively skewed than that of stock analysts, and that the market reaction to analyst reports is stronger in the bond market than in the stock market. They conclude, "Our results are consistent with bond analysts issuing more negative reports than equity analysts and providing more information about low credit quality bonds as a result of the asymmetric demand for negative information by bond investors." Finally, McCrum (2018) reports that, unlike the stock market, liquidity in the corporate bond market is limited as most bonds do not trade.

Collectively, these studies point to major dissimilarities between the stock and corporate bond markets and highlight considerable differences in the information required by investors in the two markets and in their response to information. Given these differences, the importance of aggregate Twitter opinion to the corporate bond market is unclear, notwithstanding the findings in prior research showing the important role of aggregate Twitter opinion in the stock market.

The Role of Financial Disclosures in the Corporate Bond Market

The literature on the role of financial disclosures in the corporate bond market investigates a variety of perspectives. Examining bond returns around quarterly earnings announcements, Easton et al. (2009) find that bond prices respond to quarterly earnings announcements. They document a positive association between annual bond returns and both annual changes in earnings and annual analyst forecast errors. They further show that these effects are stronger for negative earnings news and riskier bonds, consistent with the nonlinear payoff structure of bonds affecting the role of earnings in the bond market. DeFond and Zhang (2014) find that the bond price reaction to bad news is timelier than that of stock prices. They further show that speculative-grade bonds have a stronger reaction than investment-grade bonds to bad news, which suggests earnings news has a larger effect on bond prices when default risk is higher.[5] Callen et al. (2009) find that CDS spreads reflect information about default risk conveyed in earnings, cash flows, and accruals.

Gkougkousi (2014) examines the role of aggregate corporate earnings in the corporate bond market and documents a negative (positive) association between aggregate earnings changes and investment-grade (speculative-grade) corporate bond market returns. She also finds that the aggregate earnings-returns relation is lower (i.e., less positive or more negative) for bonds with higher credit ratings and longer maturities. Even-Tov (2017) finds that the bond price reaction to quarterly earnings announcements predicts post-announcement stock returns, with the predictive ability being driven by non-investment-grade bonds. Cassar et al. (2015) hypothesize and find that accrual accounting interacts with other information sources to reduce information asymmetries between small business borrowers and lenders, thereby lowering borrowers' cost of debt. Consistent with their findings, Akins (2018) provides evidence that better reporting quality is

[5] Employing small samples of only 26 and 66 firms, respectively, Hotchkiss and Ronen (2002) and Ronen and Zhou (2013) provide similar evidence of a positive bond price reaction to earnings announcement news.

associated with less uncertainty about credit risk, and that reporting quality is more important in reducing uncertainty when debt market participants have less private information. Finally, evidence by Bonsall and Miller (2017) suggests that the readability of a firm's financial disclosure influences bond market intermediaries' opinions and firms' cost of debt.

While our research question differs considerably from the questions addressed by these related studies, we consider their results when designing our analyses. Specifically, our tests include partitions of the data based on whether earnings convey negative or positive news, the riskiness of bonds, and information uncertainty underlying the bond issuer.

III. METHODOLOGY

This section delineates the methodology used to construct our dependent and test variables and outlines the research design.

Variable Definitions

The Test Variable

The test variable for our research question is the aggregate Twitter opinion, *OPI*, during the window [-10;-3], where day 0 is the earnings announcement date. We end our *OPI* measurement window on day -3 because some of our tests involve the window [-2;+2]. We focus on the window [-10;-3] because prior research documents a concentration of Twitter activity in the period just prior to quarterly earnings announcements (Ranco et al. 2015; Curtis et al. 2016; Gabrovšek et al. 2017) and because bond market participants pay attention and react to earnings news (e.g., Datta and Dhillon 1993; Easton et al. 2009; Callen et al. 2009; Defond and Zhang 2014; Ronen and Zhou 2013; Even-Tov 2017).

Along the lines of Bartov et al. (2018), we measure *OPI* using textual-analysis methodologies focusing on the words that comprise each individual tweet.[6] More specifically, *OPI* is the single factor constructed from a factor analysis using three vocabulary-based measures, each

[6] As detailed in our validity check section, we also employ an alternate measure of aggregate Twitter opinion, *OPI_BAYES*. The qualitatively similar results are tabulated in the Online Appendix (Tables OA1 to OA4).

related to a word list (or dictionary) commonly used in the literature: the Loughran and McDonald (2011) word list, the Harvard IV-4 word list, and the Hu and Liu (2004) word list. Using each word list, we compute an opinion measure as minus one multiplied by the sum of the number of negative words weighted by {1 + [Log(1 + Number of Followers)]}, scaled by one plus the number of words classified as either positive or negative. As these three underlying opinion measures are correlated, the factor analysis yields a single factor, which we label *OPI*.[7]

The Dependent Variables

Our first set of tests focuses on whether Twitter provides economically important information to the corporate bond market. To that end, we examine whether *OPI* helps predict announcement bond returns and changes in CDS spreads over a short window around earnings announcements and whether *OPI* is associated with changes in bond yield spreads over two alternative long windows.

We measure announcement bond returns, $BONDRET_{[-2;+2]}$, as buy-and-hold adjusted bond returns (multiplied by 100 for ease of presentation) over the window [-2;+2], where day 0 is the firm's quarterly earnings announcement date. To compute bond returns, we retrieve prices of all corporate bond trades during our sample period from the Trace database. We compute buy-and-hold adjusted bond returns following the methodology in Bessembinder et al. (2009), Dick-Nielsen (2009; 2014), Easton et al. (2009), and Even-Tov (2017).[8] Next, Callen et al. (2009) argue that a credit default swap (CDS) is a pure credit default instrument that provides the cleanest measure of

[7] Appendices C and D provide examples of tweets and demonstrate how the textual-analysis methodology quantifies their content. Our results hold and our inferences are unchanged when using either the individual *OPI* measures or their simple average as alternative variables.

[8] We exclude all cancelled, corrected, commission, special trades, and all trades under $100,000. We then weight each of the remaining bond trades by dollar value to compute daily clean prices for each traded bond. The Trace database compiles "clean" bond price data (prices of bond trades occurring between coupon payment dates, which already reflect the accrued interest up to the day of the trade, are "dirty" bond prices, while "clean" bond prices do not include accrued interest). Thus, we add accrued interest to calculate a daily dirty price for each traded bond, which we use in computing daily raw bond returns. We adjust each daily raw return by subtracting the risk-free rate on that day, using the return on a Treasury security with similar maturity. We require the absolute value of the daily-adjusted bond returns to be less than 20% to eliminate erroneous data.

credit risk. Consistent with Callen et al. (2009), we define the change in CDS spread, *ΔCDSSPREAD*, as a percentage of the notional principle of the underlying instrument. Following the standard in the literature (e.g., Micu et al. 2004; Ashcraft and Santos 2009; Bai and Wu 2016), we focus on five-year CDS contracts denominated in U.S. dollars with modified restructuring (MR) type documentation and senior tier, as these are the most common and liquid CDS contracts.[9] Similar to our estimation of bond returns, we measure *ΔCDSSPREAD* over the window [-2;+2], where day 0 is the firm's quarterly earnings announcement date. Lastly, we measure the change in bond yield spread, *ΔYIELD*—where bond yield spread is the difference between the yield to maturity of a traded bond and the yield to maturity of a Treasury security with a corresponding duration—over two alternative long windows: one from the last day of quarter *q*-1 to the last day of quarter *q*+1 and the other from the last day of quarter *q*-1 to the last day of quarter *q*+3, where *q* is the quarter during which *OPI* is measured. While both long windows serve to complement the short-window tests around earnings announcements, the second window compares the same fiscal quarter across years and thus is unlikely to be affected by seasonality.

For our second set of tests, the one concerning credit rating changes, we define two indicator variables, *DOWNGRADE* and *UPGRADE*, indicating, respectively, whether the traded bond exhibits a decrease or an increase in rating of S&P Global Ratings (S&P).[10] In line with our tests for changes in bond yield spreads, we measure credit rating downgrades and upgrades over two alternative long windows, the next three or nine months after the *OPI* window, [-2;+65] or [-2;+190], where day 0 is the firm's quarterly earnings announcement date .

Our third and final set of tests examines the change in implied default probability using

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[9] The MR type documentation refers to a debt restructuring clause in the CDS contract, which triggers settlement under the CDS contract. Senior tier refers to the bond instrument underlying the CDS contract.

[10] Currently there are nine registered Nationally Recognized Statistical Rating Organizations (NRSROs), overseen by the SEC's Office of Credit Ratings, which was created by the Dodd-Frank Wall Street Reform and Consumer Protection Act of July 21, 2010. In September 29, 2006, Congress passed the Credit Rating Agency Reform Act, requiring the SEC to establish guidelines for determining which credit rating agencies qualify as NRSROs. We use S&P ratings because S&P Global Ratings was the first (with Moody's Investors Service) to become an NRSRO in 1975, and because it is considered a market leader among the nine rating agencies.

three alternative approaches for estimating default probability: the Altman Z-Score (*ΔZ-PROB)*, the Ohlson O-Score (*ΔO-PROB)*, and the Black-Scholes-Merton models (*ΔBSM-PROB)*. For each approach, we measure the change in default probability (expressed in percentage), over two alternative long windows from quarter *q*-1 to either quarter *q*+1 or quarter *q*+3.

Our first approach for estimating default probability is based on Altman (1968), who combines five fundamental signals into a single index called Z-Score that measures how shielded or protected a firm is from bankruptcy. The five fundamentals relate to liquidity (working capital / total assets), retention of earnings (retained earnings / total assets), profitability (EBIT / total assets), coverage of liabilities (market capitalization / total debt), and asset turnover (sales / total assets).[11] Our second approach is based on Ohlson (1980), who develops an index (O-Score) more comprehensive than Z-Score, by including factors that either shield a firm from bankruptcy (e.g., profitability; cash flows; profitability increase), or make bankruptcy more likely (e.g., losses, negative equity). We convert the Z-Score and O-Score into probabilities by applying the logit function to the negative of the Z-Score (as higher Z-Score represents lower risk) and to the O-Score, respectively. Our third approach is based on the procedure outlined in Hillegeist et al. (2004) and Bharath and Shumway (2008) and follows from Hillegeist et al.'s (2004) finding that default risk estimates based on the option-pricing models of Black and Scholes (1973) and Merton (1974) outperform Z-Score and O-Score. Black-Scholes-Merton structurally model credit risk by viewing a company's equity as a call option on its assets. The unique inputs to this model are market-based measures, including market value of equity and stock return volatility.

Research Design

Our research question asks: does aggregate Twitter opinion convey economically important information to the corporate bond market? To study this question, we first examine

[11] The definition of *ΔZ-PROB* in Appendix A details the Altman's (1968) model and the original coefficients we employ using quarterly data. As a validity check, we alternatively calculate Z-scores using the Altman's (1968) model and either the Begley et al.'s (1996) or the Hillegeist et al.'s (2004) re-estimated coefficients. The (untabulated) results using these two alternative specifications are qualitatively similar from the tabulated results.

whether *OPI* predicts bond returns and changes in CDS spreads around the upcoming earnings announcements. We then examine whether *OPI* is associated with changes in bond yield spreads using longer window tests.

Ex-ante, the impact of Twitter information on bond returns/changes in CDS spreads is unclear. If the wisdom of crowds effect demonstrated in the stock market by Bartov et al. (2018) extends to the corporate bond market, Twitter could potentially provide information relevant to the pricing of corporate bonds. Moreover, prior research documents that bond investors misprice fundamental information (e.g., Bhojraj and Swaminathan 2009). This opens-up the possibility that Twitter information may be relevant for bond market participants. Conversely, bond investors are generally considered sophisticated, and hence any potentially relevant information on Twitter may have already reached them by the time it is posted, and hence already be largely impounded in bond prices and CDS spreads. In addition, even if Twitter information is original, it is not clear whether its effect on bond prices and CDS spreads would be large enough to allow detection among all other influences in the data. Hence, it is an empirical question as to whether aggregate Twitter opinion predicts changes in bond prices and CDS spreads. Similar arguments can be made for the association between aggregate Twitter opinion and changes in bond yields spreads.

We test whether *OPI* predicts bond returns (*BONDRET*) or changes in CDS spreads (*ΔCDSSPREAD)* using a short window around earnings announcement, by estimating the following model:

$$
\begin{aligned}
&BONDRET_{i,q,[-2;+2]} \text{ or } \Delta CDSSPREAD_{i,q,[-2;+2]} \\
&\quad = \alpha + \beta_1{*}OPI_{i,q,[-10;-3]} + \beta_2{*}FE_{i,q} + \beta_3{*}STOCKRET_{i,q,[-2;+2]} + \beta_4{*}STOCKRET_{i,q,[-10;-3]} \\
&\quad + \beta_5{*}RP\_OPI_{i,q,[-10;-3]} + \beta_6{*}LEV_{i,q} + \beta_7{*}ROA_{i,q} + \beta_8{*}SIZE_{i,q} + \beta_9{*}MB_{i,q} + \beta_{10}{*}ANL_{i,q} \quad (1) \\
&\quad + \beta_{11}{*}INST_{i,q} + \beta_{12}{*}Q4_{i,q} + \beta_{13}{*}LOSS_{i,q\text{-}1} + \beta_{14}{*}HORIZON_{i,q} + \beta_{15}{*}RATING_{i,q} \\
&\quad + \beta_{16}{*}SPEC_{i,q} + \beta_{17}{*}SUBORD_{i,q} + \Sigma\delta_j{*}IND_j + \Sigma\delta_f{*}CALQTR_f + \varepsilon_{i,q,[-2;+2]}
\end{aligned}
$$

The dependent variable for our long-window tests is changes in bond yield spreads (*ΔYIELD*), and the model contains a subset of the variables used for the short-window tests, as follows:

$$
\begin{aligned}
&\Delta YIELD_{i,[q\text{-}1;q+k]} = \alpha + \beta_1{*}OPI_{i,q,[-10;-3]} + \beta_2{*}FE_{i,q} + \beta_3{*}STOCKRET_{i,q,[-2;+2]} \\
&\quad + \beta_4{*}STOCKRET_{i,q,[-10;-3]} + \beta_5{*}RP\_OPI_{i,q,[-10;-3]} + \beta_6{*}LEV_{i,q} + \beta_7{*}ROA_{i,q} \quad (2)
\end{aligned}
$$

$$+ \beta_8{*}SIZE_{i,q} + \beta_9{*}MB_{i,q} + \beta_{10}{*}HORIZON_{i,q} + \beta_{11}{*}RATING_{i,q} + \beta_{12}{*}SPEC_{i,q}$$
$$+ \beta_{13}{*}SUBORD_{i,q} + \Sigma\delta_j{*}IND_j + \Sigma\delta_f{*}CALQTR_f + \varepsilon_{i,[q\text{-}1;q+k]}$$

If aggregate Twitter opinion is economically meaningful in the bond market, we expect positive (negative) news in *OPI* to lead to positive (negative) bond returns. Hence, when the dependent variable is *BONDRET*, we expect β_1, the coefficient on *OPI*, in Equation (1) to be significantly positive. Likewise, we expect positive (negative) news in *OPI* to lead to reduced (increased) CDS/bond yield spreads. Hence, we expect β_1 in Equations (1) and (2) to be significantly negative when the dependent variable is, respectively, *ΔCDSSPREAD* and *ΔYIELD*.

An association between aggregate Twitter opinion and changes in bond/CDS prices or bond yield spreads may be driven by the corporate bond market learning from earnings news and/or the stock market reaction to earnings announcements. Indeed, Bartov et al. (2018) show that aggregate Twitter opinion helps predict earnings and announcement stock returns. We thus include in Equations (1) and (2) two control variables: earnings surprise (*FE*) and announcement stock returns ($STOCKRET_{[-2;+2]}$). *FE* is the I/B/E/S reported quarterly earnings per share less the latest consensus analyst quarterly earnings per share forecast just prior to the quarterly earnings announcement date, scaled by the stock price as of the forecast date (multiplied by 100). $STOCKRET_{[-2;+2]}$ is Carhart's (1997) four factor buy-and-hold abnormal stock returns (multiplied by 100) over the window [-2;+2], where day 0 is the firm's quarterly earnings announcement date. Based on the findings and discussion in Datta and Dhillon (1993, Table 3), we expect the coefficients on *FE* and $STOCKRET_{[-2;+2]}$ to be positive in Equation (1) when the dependent variable is *BONDRET* and negative in Equations (1) and (2) when the dependent variable is *ΔCDSSPREAD* and *ΔYIELD*, respectively. However, the effect of each variable may be reduced due to the positive correlation between these two variables.

To control for other information that reaches the capital markets during the window [-10;-3] and may confound our findings, we introduce two additional variables. $STOCKRET_{[-10;-3]}$ is the Carhart's (1997) four factor buy-and-hold abnormal stock returns for the firm over the window [-10;-3] (multiplied by 100). *RP_OPI* is a measure of the aggregate opinion from traditional news over the window [-10;-3], retrieved from the RavenPack database. This variable controls for concurrent information and opinion from traditional news media (e.g., print magazines and newspapers), notwithstanding major differences between traditional news media and social media, including quality, reach, frequency, usability, immediacy, permanence, and way of operation (one source to many receivers as opposed to many sources to many receivers). The coefficient on $STOCKRET_{[-10;-3]}$ is expected to be positive (negative) in Equation (1) when the dependent variable is *BONDRET* (*ΔCDSSPREAD*), and negative in Equation (2) when the dependent variable is *ΔYIELD*, if stock prices lead bond prices/yields and CDS spreads.

We control for firm characteristics by including the following four variables. *LEV*, our measure of leverage, is total debt scaled by total assets. *ROA*, our measure of profitability, is net income before extraordinary items scaled by average total assets. *SIZE*, our measure of firm size, is the natural logarithm of market value of equity. *MB* is the market-to-book ratio. We control for bond characteristics using the following four variables. *HORIZON* is the number of days between the quarterly earnings announcement date and the traded bond's maturity date. *RATING* is the S&P rating converted to a numerical scale from 1 to 22 (AAA = 1, AA+ = 2, …, D = 22). *SPEC* is an indicator variable equal to one if the traded bond has a S&P rating below BBB-, zero otherwise. *SUBORD* is an indicator variable equal to one for firms with at least one subordinated bond, zero otherwise. If a firm has more than one traded bond, *HORIZON*, *RATING*, and *SPEC* are aggregated at the firm-quarter level using value-weighted means. Finally, for the short-window tests, we include four control variables shown by prior research to relate to capital market participants' reaction around earnings announcements: *ANL*, the number of analysts in consensus I/B/E/S/ quarterly earnings forecast; *INST*, institutional investor holding; *Q4*, an indicator variable for the fourth fiscal quarter; and *LOSS*, an indicator variable for past quarterly loss. In addition, all specifications include industry and calendar quarter fixed effects, as Chava and Jarrow (2004) document the importance of including industry fixed effects for credit risk analysis. Appendix A provides additional details regarding the definition and computation of our variables.[12]

Next, we test whether aggregate Twitter opinion reflects the information used by information intermediaries, more specifically credit rating agencies (e.g., S&P, Moody's, and Fitch). Credit rating agencies help bond market participants evaluate credit risk, price debt securities, as well as create a robust secondary market for those issues, by providing high-quality, objective, value-added analytical information to the market. However, the agencies, whose credit ratings principally rely on the public information provided by the rated company, do not perform an audit of the rated company's books, or otherwise take upon themselves to verify information provided by the rated company. Instead, they rely on the integrity and quality of the rated company's publicly available financial statements.[13] Indeed, there have been documented cases of rating agencies ignoring emerging relevant sources of information, e.g., their failure to incorporate signals from the CDS market in a timely fashion when rating mortgage-backed securities during the financial crisis in 2007-2008. In contrast, Twitter users may rely on information other than financial statement information, and consequently may provide information not reflected in ratings. Another potential advantage of Twitter information is that it benefits from the wisdom of crowds. Thus, Twitter might potentially provide information incremental to the information set used by these rating agencies, and hence be associated with changes in credit ratings. This motivates our second set of tests, which consists of a multinomial logit model that considers the possibility of either a downgrade or an upgrade in credit ratings.[14] Specifically, we estimate the following specification:

$$\log\left(\frac{\Pr(\Delta RATING_{i,[-2;+t]} = -1, 1)}{\Pr(\Delta RATING_{i,[-2;+t]} = 0)}\right) = \alpha + \beta_1 * OPI_{i,q,[-10;-3]} + \beta_2 * FE_{i,q} + \beta_3 * STOCKRET_{i,q,[-2;+2]}$$

[12] We examine the sensitivity of our results to specifications that consider changes in the control variables, instead or in addition to levels, and find our results (tabulated in the Online Appendix, Tables OA13 to OA15) are robust.

[13] For more details, see "U.S. Securities and Exchange Commission Public Hearing - November 15, 2002: Role and Function of Credit Rating Agencies in the U.S. Securities Markets," at: https://www.sec.gov/news/extra/credrate/standardpoors.htm, accessed March 15, 2022.

[14] Results (not tabulated for parsimony) are nearly indistinguishable if we estimate separate logistic regressions for credit rating downgrades or upgrades.

$$+ \beta_4{*}STOCKRET_{i,q,[-10;-3]} + \beta_5{*}RP\_OPI_{i,q,[-10;-3]} + \beta_6{*}LEV_{i,q} + \beta_7{*}ROA_{i,q} + \beta_8{*}SIZE_{i,q} + \beta_9{*}MB_{i,q} + \beta_{10}{*}HORIZON_{i,q} + \beta_{11}{*}RATING_{i,q} + \beta_{12}{*}SPEC_{i,q} + \beta_{13}{*}SUBORD_{i,q} + \Sigma\delta_j{*}IND_j + \Sigma\delta_f{*}CALQTR_f + \varepsilon_{i,[-2;+t]} \quad (3)$$

where $\Delta RATING_{[-2;+t]}$ (t = 65 or 190) is either equal to minus one if a traded bond has a credit rating downgrade, equal to one if a traded bond has an upgrade, and zero if there is no change in credit rating. This specification allows for the possibility of either a downgrade or an upgrade in the three or nine months after the *OPI* window. If aggregate Twitter opinion is associated with changes in credit ratings, we expect β_1 in Equation (3), the coefficient on *OPI*, to be significantly negative for downgrades and significantly positive for upgrades. A significant association between *OPI* and credit rating changes would suggest that either credit rating agencies utilize the aggregate Twitter opinion in their credit rating decisions or the information they use is correlated with the Twitter information. We also introduce variables that control for possible confounding effects, namely earnings news, stock market reaction, information from sources other than Twitter, firm characteristics, and bond characteristics. The control variables and fixed effects are the same as Equation (2), as the dependent variables are measured over similar windows. We measure the rating changes over two alternative long windows, three or nine months, as opposed to a short window around earnings announcements, because rating agencies follow a bureaucratic process and do not necessarily update ratings continuously.

Finally, we assess the nature of the information conveyed by *OPI* to the corporate bond market. As discussed earlier, for Twitter information to be potentially useful, it must be forward looking and valuation relevant to bond market participants. For bond market participants, predicting default is of prime interest (Hillegeist et al. 2004; Beaver et al. 2011; Akins 2018). We thus test whether aggregate Twitter opinion is associated with future changes in default risk by estimating the following model:

$$\Delta PROB_{i,[q-1;q+k]} = \alpha + \beta_1{*}OPI_{i,q,[-10;-3]} + \beta_2{*}FE_{i,q} + \beta_3{*}STOCKRET_{i,q,[-2;+2]} + \beta_4{*}STOCKRET_{i,q,[-10;-3]} + \beta_5{*}RP\_OPI_{i,q,[-10;-3]} + \beta_6{*}LEV_{i,q} + \beta_7{*}ROA_{i,q} + \beta_8{*}SIZE_{i,q} + \beta_9{*}MB_{i,q} + \beta_{10}{*}HORIZON_{i,q} + \beta_{11}{*}RATING_{i,q} + \beta_{12}{*}SPEC_{i,q} + \beta_{13}{*}SUBORD_{i,q} + \Sigma\delta_j{*}IND_j + \Sigma\delta_f{*}CALQTR_f + \varepsilon_{i,[q-1;q+k]} \quad (4)$$

where *ΔPROB* is either *ΔZ-PROB*, *ΔO-PROB* or *ΔBSM-PROB*, and *k* equals one or three. If aggregate Twitter opinion is associated with future changes in default risk, we would expect β_1 in Equation (4), the coefficient on *OPI*, to be significantly negative (i.e., more positive Twitter opinion is associated with lowered default risk and vice versa). In addition to our test variable (*OPI*), similar to Equations (2) and (3), Equation (4) contains variables and fixed effects that control for possible confounding effects, namely earnings news, stock market reaction, information from sources other than Twitter, firm characteristics, and bond characteristics.

IV. DATA

Sample Selection

Our sample consists of historical Twitter data, purchased from Gnip, a provider of social data and analytics (now a subsidiary of Twitter). We use Twitter data to test our hypotheses for two primary reasons. First, Twitter information is rich and encompasses numerous and widely diverse opinions, suggesting it may cover many aspects of firm attributes of interest not only to equity investors, but also to bond investors. In addition, this wide diversity—which makes the opinions less likely to exhibit herding, a phenomenon that plagues traditional information intermediaries (e.g., financial analysts), as well as social media platforms (e.g., blogs, investing portals) that post a central piece of information on which users comment—allows users to tap into the Wisdom of Crowds, where the aggregation of information provided by many (non-expert) individuals often predicts outcomes more precisely than experts. Second, Twitter's short format (initially up to 140 characters, now 280 characters) and ease of information search (e.g., the use of cashtags) make it an ideal medium to share information in a timely fashion, in contrast to the longer format and potentially reduced timeliness of research reports or articles. Still, we acknowledge that the information in tweets may be uninformative or even misleading for two reasons. First, Twitter is an unregulated platform with potentially uninformed anonymous users. Second, much of the discussion on Twitter may pertain to stocks' prospects and prices, particularly with the use of the cashtag ("$" prefix) placed before a ticker symbol to refer to a firm's stock. Twitter information may hence only be indirectly relevant to bond market participants, and consequently may have only a second- or perhaps even a third-order effect in predicting bond riskiness and value, which, in turn, may be hard to detect among all other influences in the data.

Our data comprise the full archive of tweets with cashtags, i.e., stock symbols preceded by the dollar sign (e.g., $AAPL for Apple; $PEP for PepsiCo). We limit our sample to tweets with cashtags in an effort to increase confidence that the tweets relate to the firm financial performance and value, thereby increasing the relevance of our measures. We use the Trace database to obtain corporate bond transaction information (e.g., bond prices, bond yield spreads), the Markit database for CDS contract data, and the Mergent Fixed Income Securities (FISD) database to gather bond-issuance information (e.g., issue size, issue date, bond features) and other bond-specific information (e.g., coupon rate, frequency of coupon payment, bond ratings). We retrieve the data on opinions expressed in traditional media channels from the RavenPack database. Finally, we retrieve accounting, stock price, analyst forecast, and institutional ownership data, respectively, from the Compustat quarterly, CRSP daily stock, I/B/E/S, and Thomson-Reuters 13F databases.

Table 1 presents the effects of our sample selection process on the sample size. Our initial sample contains 10,894,037 tweets (66,290 firm-quarters from 4,733 unique firms) with cashtags from Russell 3000 firms between March 21, 2006 and December 31, 2012. Following Da et al. (2011), we consider all stocks ever included in the Russell 3000 Index during our sample period. We drop tweets containing multiple stock symbols to know precisely which firm each tweet refers to, reducing the sample to 8,713,182 tweets (61,357 firm-quarters; 4,668 unique firms). Next, we require that the firms mentioned in the tweets have Compustat data, decreasing our sample size to 8,674,195 tweets (60,638 firm-quarters; 4,596 unique firms). We then exclude tweets prior to December 17, 2008 due to limited Twitter activity and limited use of cashtags in Twitter prior to

2009, reducing the sample to 8,462,761 tweets (54,906 firm-quarters; 4,132 unique firms).[15]

Given the focus of this paper, we only consider tweets pertaining to firms with traded bonds for which bond returns are available, which reduces the sample size to 3,139,188 tweets (9,717 firm-quarters; 1,193 unique firms). We then manually clean the list of ticker symbols and cashtags in our sample to eliminate observations that do not represent tweets about stock tickers.[16] This results in a sample of 2,692,185 tweets (9,404 firm-quarters; 1,158 unique firms). Our next data filter is crucial: we focus on tweets that mention words and phrases either related to bonds, credit risk, firm fundamentals or securities trading. We screen for tweets related to bonds and credit risk using the credit risk dictionary from Sethuraman (2019) augmented with additional words and phrases inspired from Campbell et al. (2014), while we use the list of words and phrases related to both fundamentals and securities trading from Bartov et al. (2018). This ensures that the tweets provide information relevant to debt securities and results in a sample of 2,159,448 tweets (9,347 firm-quarters; 1,158 unique firms). Finally, to ensure that Twitter information is more likely to contain fundamental information, we focus on tweets from the eight-trading-day period [-10;-3] prior to quarterly earnings announcements (day 0), released over the period January 1, 2009 to December 31, 2012. The final sample consists of 232,930 tweets from 25,502 distinct users, corresponding to 7,356 firm-quarters and representing 1,037 unique firms.[17] As firms can have more than one traded bond, these 7,356 firm-quarters correspond to 29,287 bond-quarters.

Sample Descriptive Statistics

Table 2 presents sample distribution of tweets, bond-quarters, and firm-quarters by calendar quarter (Panel A) and industry (Panel B). Panel A documents an increase in Twitter

[15] The sample period begins ten trading days before January 1, 2009 because our test variable, *OPI*, is computed during the window [-10;-3]. The sample period ends on December 31, 2012, the end of our Twitter data.

[16] We delete tweets in which the ticker symbol mentioned has a generic meaning and does not refer to a company's stock (e.g., $CASH, $GDP, $M, etc.), as well as tweets in which the ''$'' symbol is used not as a cashtag, but rather to refer to a generic word (e.g., $ALE for sale; $LOW for slow; $WAG for swag).

[17] The Twitter user accounts in our sample are labelled as "person." While this provides assurance that the tweets are from individuals, and not company accounts, the identities of the users are not beyond doubt as most of the identifying information is self-reported.

activity over our sample period, with tweets per calendar quarter increasing from 673 tweets in the first quarter of 2009 to 40,551 tweets in the second quarter of 2012. This pattern reflects the increased popularity of social media during our sample period. Parallel to the increase in tweets, the numbers of bond-quarters and firm-quarters also increase substantially, respectively from 837 and 146 in the first quarter of 2009 to 2,257 and 610 in the fourth quarter of 2012.

Panel B of Table 2 presents comparisons of the sample distributions of tweets, bond-quarters, and firm-quarters with that of the Compustat universe across 48 Fama and French (1997) industry groupings. Our samples of tweets, bonds, and firms span all industries, with a distribution across industries fairly similar to the Compustat universe and little evidence of industry clustering.

Descriptive Statistics for the Regression Analysis Variables

Panel A of Table 3 presents descriptive statistics for the variables used in our regressions. Our opinion variable, *OPI*, derived from factor analysis, has a mean close to zero (0.005), by construction, and a higher median of 0.467. $BONDRET_{[-2;+2]}$ has a positive mean and median of 0.118% and 0.074%, respectively. *ΔCDSSPREAD*, which moves in the opposite direction as bond returns, has a negative mean (-0.412%) and median (-0.278%). Similarly, *ΔYIELD* has negative means (-0.173 and -0.095) and medians (-0.230 and -0.248) over the [*q*-1;*q*+1] and [*q*-1;*q*+3] windows, respectively. The incidence of bond downgrades (4.6%) is higher than upgrades (4.0%) over the [-2;+65] window, but identical (10.3%) over the [-2;+190] window. Our proxies for changes in default risk (*ΔZ-PROB*, *ΔO-PROB*, and *ΔBSM-PROB*) have means (medians) ranging from -3.796% to 0.037% (-0.125% to 0.001%) and show considerable variation. For example, $\Delta Z\text{-}PROB_{[q-1;q+1]}$ is -1.810% at the first quartile and 1.442% at the third quartile. Interestingly, the mean (median) forecast error, *FE*, is close to zero at 0.014% (0.070%). $STOCKRET_{[-2;+2]}$, the announcement stock returns, has a small negative mean (median) of -0.125% (-0.098%), while $STOCKRET_{[-10;-3]}$, the stock returns during the *OPI* window, has a small positive mean (median) of 0.283% (0.277%). *RP_OPI*, the proxy for aggregate opinion from traditional news media, has a negative mean of -0.135, consistent with overall pessimism in traditional media (Tetlock 2007;

Engelberg 2008). Furthermore, *RP_OPI* exhibits a relatively low standard deviation (0.187) compared to that of *OPI* (0.985), suggesting more divergence of opinion in Twitter.

The statistics of our two firm size measures, *ASSETS* (mean = 40,978 $million; median = 9,817 $million) and *MVE* (mean = 17,596 $million; median = 6,351 $million), suggest that the sample consists of large firms, which is not surprising given the requirement that they have traded bonds. The mean (2.8) and median (1.8) *MB*, the market-to-book ratio, suggest the sample includes a relatively small number of intangible-intensive firms whose *MB* tends to be higher. The sample also consists of firms in relatively strong information environments, as evidenced by the mean *ANL* of 2.5, which corresponds to over eleven analysts, and the first quartile of *ANL*, 2.2, which corresponds to over eight analysts (*ANL* is the natural logarithm of one plus the number of analysts). The average firm has 72.5% of its shares held by institutional investors (median = 78.6%), indicating sophisticated ownership dominates our sample. Finally, just under a quarter of our sample (23.6%) corresponds to earnings announcements of fourth-quarter results (*Q4*), while less than a fifth of our sample (19.7%) reports a quarterly loss in the previous quarter.

The bond characteristics suggest that sample firms have traded bonds with a mean (median) horizon of 3,165 (2,494) days. The mean (median) rating is 10.8 (10.0) which is just above investment grade. 43.5% of all firm-quarters have speculative-grade (i.e., non-investment grade) bonds. Finally, 16.3% of firm-quarters have at least one subordinated traded bond.

Correlation Coefficients

Panel B of Table 3 presents pairwise correlation coefficients among the key test variable, *OPI*, and the dependent variables for our models outlined above. Figures above and below the diagonal represent, respectively, Spearman and Pearson correlations. *OPI* has a significantly positive correlation with $BONDRET_{[-2;+2]}$ and significant negative correlations with *ΔCDSSPREAD* and *ΔYIELD*. In addition, consistent with the nonlinear payoff structure of bonds, *OPI* is significantly negatively correlated with *DOWNGRADE*, but either insignificantly or positively correlated with *UPGRADE*. Overall, this suggests aggregate Twitter opinion is economically important for bond market participants. In addition, *OPI* has significantly negative correlations with the changes in implied default probability measures (*ΔZ-PROB*, *ΔO-PROB*, and *ΔBSM-PROB).* This may be viewed as *prima facie* evidence of an association between aggregate Twitter opinion and future changes in default risk.

Panel C provides the correlation matrix between *OPI* and the control variables used in our regression analyses. Not surprising, the correlation between *OPI* and *RP_OPI*, is modest, only 0.13 (Spearman) and 0.12 (Pearson). Still, the two correlation coefficients are highly statistically significant (p-values < 0.01), reinforcing the importance of controlling for aggregate opinion in traditional media. Overall, the small pairwise correlation coefficients among our control variables indicate that there is little evidence of a multi-collinearity problem in our data (one notable exception is *SIZE*, which, as might be expected, is positively correlated with *ROA* and *ANL*, and negatively correlated with *LOSS*, *RATING*, and *SPEC*).

V. EMPIRICAL RESULTS

Does Aggregate Twitter Opinion Convey Economically Important Information?

To examine whether Twitter conveys economically meaningful information to the corporate bond market, we first estimate Equation (1) for the full sample and for two subsamples partitioned by the sign of the earnings news, positive or negative. The dependent variable is either bond returns (*BONDRET*) or changes in CDS spreads (*ΔCDSSPREAD*), measured in the [-2;+2] window around earnings announcements. The results are presented in Table 4, Panel A. The first three columns use *BONDRET* as the dependent variable. In the full sample, we find that *OPI* has a significantly positive coefficient on 0.053 (t-statistic = 3.18). Recall that the regression controls for a number of possible confounds including the earnings forecast error (*FE*) and the stock market reaction to the earnings news ($STOCKRET_{[-2;-+2]}$).[18] This suggests that the ability of *OPI* to predict

[18] It is important to control for contemporaneous stock returns in a test with bond returns as a dependent variable because prior research, notably Fama and French (1993) and Even-Tov (2017), documents a positive correlation between stock returns and bond returns around earnings announcements.

announcement bond returns is incremental to any mechanical association with the stock market reaction. The interquartile range of *OPI* in the sample of 6,862 observations included in this regression is 1.526 (0.803 minus -0.723). From an economic significance perspective, a coefficient on *OPI* of 0.053 implies a difference in *BONDRET* between observations in the 25th and 75th percentiles of the *OPI* distribution of 0.081% (= 1.526*0.053), i.e., 8.1 basis points over a five-day window, which translates into 4.16% annualized returns.

Easton et al. (2009) find that the corporate bond market is more sensitive to bad news as opposed to good news and ascribe this finding to the nonlinear payoff structure of bonds. Using the realized earnings forecast error (*FE*) as a proxy for news, we partition our sample into bad news ($FE < 0$) and good news ($FE \geq 0$) subsamples and rerun our tests. The results, presented in the next two columns of Table 4, Panel A, show, as expected, that the effect of *OPI* on announcement bond returns is stronger for bad news than for good news. The coefficient on *OPI* is 0.140 (*t*-statistic = 3.55) in the bad news subsample, but only 0.015 (*t*-statistic = 0.76) in the good news subsample, with a significant difference of 0.125 (*t*-statistic = 2.85).[19] Since the *OPI* window precedes the earnings announcement, one way to interpret these findings is that bond market participants seem to weight past Twitter opinion based on the *ex post* sign of the earnings news revealed by the earnings announcement. This interpretation would imply bond investors react to Twitter information in a delayed fashion conditional on the revelation of the sign of the earnings news.

The three right-most columns of Table 4, Panel A, repeat the analysis with $\Delta CDSSPREAD_{[-2;+2]}$ as the dependent variable. Consistent with the *BONDRET* results, we find a significantly negative coefficient on *OPI* of -0.438 (*t*-statistic = -3.68) for the full sample. This coefficient represents a decrease in CDS spreads of 0.665% (= 1.518*-0.438), over the earnings announcement window, for an interquartile increase in *OPI* (0.757 minus -0.761, in the sample of

[19] The significance of the difference in the coefficients is computed using a differences-in-means test with a pooled estimate of standard error.

3,500 observations). In comparison, the sample mean and median change in CDS spreads are only -0.434% and -0.280%, respectively. We also find a stronger association for bad news (coefficient on *OPI* = -0.816; *t*-statistic = -2.72) than for good news (coefficient on *OPI* = -0.224; *t*-statistic = -1.71), with a marginally significant difference of -0.592 (*t*-statistic = -1.81). Overall, the results in Table 4, Panel A, support that aggregate Twitter opinion predicts upcoming announcement bond returns and changes in CDS spreads, primarily when firms are experiencing bad news.

We next carry out cross-sectional tests to determine whether the ability of *OPI* to predict announcement bond returns and changes in CDS spreads is stronger in settings where *OPI* may have a more salient role. Our first partition is based on the contents of the tweets. Recall that our sample includes tweets pertaining to bonds, credit risk, firm fundamentals, and/or securities trading. If the tweets contain information directly pertinent to bonds or credit risk, they should elicit a stronger response from the bond market than tweets pertaining to firm fundamentals or trading. For each firm-quarter observation, we thus calculate the proportion of tweets that are related to bonds and/or credit risk (*%BOND*) and partition the sample into subsamples of high and low *%BOND*. We then estimate Equation (1) for the two partitions. The results are presented in Panel B of Table 4.[20] As the results indicate, the ability of *OPI* to predict both announcement bond returns and changes in CDS spreads is significantly stronger when a greater portion of the tweets pertains specifically to bond and/or credit risk information. For instance, in the regression for *BONDRET*, the coefficient on *OPI* is positive, 0.100, and highly significant (*t*-statistic = 4.30) for the high *%BOND* subsample and insignificant -0.003 (*t*-statistic = -0.12) for the low *%BOND* tweet subsample, with the difference between these two coefficients, 0.103, being highly significant (*t*-statistic = 2.85). We find similar results for *ΔCDSSPREAD*.

Our next partition is motivated by findings in prior research that indicate speculative-grade bond prices show a greater sensitivity to news than investment-grade (e.g., Gkougkousi 2014;

[20] In Panels B, C, and D of Tables 4-7, only the results for *OPI* coefficients are presented. For parsimony, coefficients on the control variables are not reported.

Even-Tov 2017), suggesting that the ability of *OPI* to predict announcement bond returns/changes in CDS spreads should be more pronounced for speculative-grade bonds than investment-grade bonds. We test this by estimating Equation (1) for subsamples of speculative-grade and investment-grade bonds. Panel C of Table 4 displays the results. We find positive (negative) coefficients on *OPI* for announcement bond returns (changes in CDS spreads) for both subsamples. The differences in coefficients between the two subsamples are statistically insignificant, however.

Our final partition is motivated by Akins (2018), who documents that higher reporting quality is associated with less uncertainty about credit risk. Twitter information may thus provide greater incremental information for firms with high information uncertainty (i.e., lower reporting quality) and higher uncertainty about credit risk. Consistent with prior research (Jiang et al. 2005; Zhang 2006), we use stock return volatility to measure information uncertainty and estimate Equation (1) for subsamples of high and low uncertainty. The results are presented in Panel D of Table 4. Consistent with our conjecture, the ability of *OPI* to predict *BONDRET* is stronger in the high information uncertainty subsample. The coefficient on *OPI* for the high uncertainty subsample is 0.091 (*t*-statistic = 2.86) as opposed to 0.022 (*t*-statistic = 1.24) for the low uncertainty subsample, with the difference between the coefficients, 0.069, being marginally significant (*t*-statistic = 1.90). This is consistent with the evidence in Akins (2018) and suggests that the salience of information from Twitter for debt investors increases with information uncertainty. However, when we repeat the analysis using *ΔCDSSPREAD*, we do not find a significant difference in the coefficient on *OPI* between the two subsamples.

To complement our short-window tests, we employ Equation (2) that estimates the association between *OPI* and changes in bond yield spreads (*ΔYIELD*) over two alternative windows, [*q*-1;*q*+1] and [*q*-1;*q*+3], where *q* is the quarter where *OPI* is measured.[21] In Equation

[21] The bond yield spread is the difference between the yield to maturity of a traded bond and the yield to maturity of a Treasury security with a corresponding duration. If a firm has more than one traded bond, we calculate the weighted average yield spread of the individual bonds. The yields on Treasury securities are from the H.15 release published by the Federal Reserve Bank of New York.

(2), we expect the coefficient on *ΔYIELD* to be negative, as more positive news in *OPI* would be associated with lower bond yield spreads. The results are presented in Table 5. As before, Panel A presents the results for the entire sample, and Panels B, C, and D the results from cross-sectional analyses. Consider the results in Panel A first. The coefficients on *OPI* for both windows are significantly negative. For [*q*-1;*q*+1], the coefficient on *OPI* is, as expected, negative (-0.166) and highly significant (*t*-statistic = -3.29). Likewise, for [*q*-1;*q*+3], the coefficient on *OPI* is negative, -0.269, and highly significant (*t*-statistic = -3.58). These coefficients represent a decrease in bond yield spreads of 0.259 (= 1.562*-0.166) and 0.425 (= 1.580*-0.269), over the windows [*q*-1;*q*+1] and [*q*-1;*q*+3], respectively, for an interquartile increase in *OPI* (i.e., 0.758 minus -0.804, and 0.757 minus -0.823, in the samples of 5,402 and 5,228 observations, respectively). In contrast, the sample mean (median) change in bond yield spreads is only -0.145 (-0.224) and -0.083 (-0.239), respectively.

We next carry out cross-sectional tests to determine whether the association between *OPI* and *ΔYIELD* is stronger in settings where *OPI* is expected to have a more salient effect. Specifically, we re-estimate Equation (2) using the same three partitions used in Table 4.[22] Table 5, Panel B, presents results for subsamples of high and low proportions of bond/credit risk-related tweets. Consistent with expectations, we find a significantly negative coefficient on *OPI* for the high *%BOND* subsample (coefficient = -0.210; *t*-statistic = -3.27), while the coefficient on *OPI* for the low *%BOND* subsample is insignificant (coefficient = -0.120; *t*-statistic = -1.40). Contrary to the results in Panel B of Table 4, however, the difference between these two *OPI* coefficients is insignificant. Table 5, Panel C, tests whether the association between *OPI* and *ΔYIELD* is more pronounced for speculative-grade bonds as opposed to investment-grade bonds. While *OPI* is significantly associated with *ΔYIELD* for both speculative-grade and investment-grade bonds, as expected the coefficient on *OPI* is significantly larger for speculative-grade bonds (-0.362; *t*-

[22] Panels B, C, and D of Tables 5 and 7 (Table 6) present only the results for the [*q*-1;*q*+1] ([-2;+65]) window. The results for the [*q*-1;*q*+3] ([-2;+190]) window are similar and not tabulated for parsimony.

statistic = -2.73) than for investment-grade bonds (-0.127; *t*-statistic = -3.98), with the difference between these two coefficients, -0.235 being marginally significant (*t*-statistic = -1.72). Panel D partitions our sample on the basis of information uncertainty. Consistent with our conjecture, the association between *OPI* and *ΔYIELD* is significantly more pronounced for the high information uncertainty subsample. The coefficient on *OPI* for the high uncertainty subsample is -0.380 (*t*-statistic = -4.20) as opposed to -0.061 (*t*-statistic = -0.86) for the low uncertainty subsample, with the difference between these coefficients, -0.319, being highly significant (*t*-statistic = -2.77). Collectively, the results from Tables 4 and 5 support our conjecture that Twitter reflects information used by investors in the corporate bond market.

Aggregate Twitter Opinion and Future Changes in Credit Ratings

Our results thus far suggest that aggregate Twitter opinion provides economically meaningful information to the corporate bond market, as it is associated with announcement bond returns, changes in CDS spreads, and changes in bond yield spreads. Our second set of tests examines whether Twitter information is associated with changes in credit ratings. We examine this by estimating a multinomial logit specified in Equation (3) that considers the likelihood of either a downgrade or an upgrade in S&P credit ratings in the three or nine months after the *OPI* window.

Table 6, Panel A, presents the results, where the coefficients for downgrades and upgrades are presented side-by-side. As the results indicate, *OPI* is strongly negatively associated with downgrades, but insignificantly related to upgrades. To illustrate, for the window [-2;+65], the coefficients on *OPI* for downgrades is -0.250 (*t*-statistic = -3.97), while the coefficient for upgrade is only -0.066 (*t*-statistic = -1.00). The difference between these two coefficients, -0.184, is significant (*t*-statistic = -2.01). The results are almost identical for the longer window [-2;+190]. These results suggest that aggregate Twitter opinion provides information that is incremental to that reflected in the credit ratings, but only for rating downgrades.[23] This is consistent with the results in prior literature and our earlier results that suggest a greater relevance of negative information in the corporate bond market, as well as with the findings in Gu and Kurov (2020) that tweets provide new information about analysts' stock recommendations and price targets.

We next test whether the association between Twitter information and credit rating changes is stronger in settings where such information is likely to have greater salience—i.e., for observations with greater bond-related tweets, for speculative bonds, and in settings of high information uncertainty. Table 6, Panel B, presents the results for subsamples of high and low proportions of bond/credit risk-related tweets. *OPI* is significantly associated with credit rating downgrades in the high *%BOND* subsample (coefficient = -0.278; *t*-statistic = -3.32) as well as in the low *%BOND* subsample (coefficient -0.199; *t*-statistic -2.07). The difference between the coefficients, -0.078, however, is insignificant (*t*-statistic = -0.61). There is an insignificant difference between the coefficients on *OPI* for *UPGRADE*, with the coefficients being insignificant for both subsamples. Table 6, Panel C, presents the results for the partition based on speculative-grade and investment-grade bonds. As expected, *OPI* is significantly negatively associated with credit rating downgrades for speculative bonds (coefficient = -0.356; *t*-statistic = -3.77), while the association is insignificant for investment-grade bonds (coefficient = -0.107; *t*-statistic = -1.20). The difference between the two coefficients, -0.249, is significant (*t*-statistic = -1.92). For credit rating upgrades, *OPI* coefficients and differences are insignificant. Finally, Table 6, Panel D, presents the results for the partition based on information uncertainty. *OPI* is significantly negatively associated with credit rating downgrades for both high information uncertainty (coefficient = -0.247; *t*-statistic = -3.06) and low information uncertainty (coefficient

[23] To be sure, our results do not necessarily imply that credit rating agencies rely on the aggregate Twitter opinion when revising their ratings. It is possible that, in their credit rating decisions, they utilize other information that is associated with the Twitter information.

= -0.187; *t*-statistic = -2.03) subsamples. The difference between the coefficients is insignificant at -0.059 (*t*-statistic = -0.48), however. For credit rating upgrades, as before, the coefficients on *OPI* are insignificant for both subsamples, as is the difference between the coefficients.

Overall, the results in Table 6 offer additional insight into how Twitter information conveys economically meaningful information to the corporate bond market by providing evidence of an association between *OPI* and future credit rating changes. Specifically, the findings suggest that Twitter information is relevant for credit rating downgrades but not for upgrades, consistent with the nonlinear payoff structure of bonds. Further, the information is particularly relevant for speculative bonds as opposed to investment-grade bonds. Interestingly, the information is relevant for subsamples with high and low proportions of bond/credit risk-related tweets as well as in settings of high and low information uncertainty. This highlights that Twitter provides information pertaining to future credit rating changes in all settings, even where Twitter opinion is less expected to play a salient role (i.e., low proportions of bond/credit risk-related tweets and low information uncertainty).

Aggregate Twitter Opinion and Future Changes in Default Risk

Our third and final set of tests examines the nature of the Twitter information underlying our findings by examining whether aggregate Twitter opinion is associated with future changes in default risk. To that end, we estimate Equation (4), which regresses changes in implied default probability on *OPI* and control variables. Table 7 reports the results for the full sample (Panel A) and from cross-sectional analyses (Panels B-D). Consider the results in Panel A first. The first two columns present results using *ΔZ-PROB* as the dependent variable for [*q*-1;*q*+1] and [*q*-1;*q*+3]. In both regressions, *OPI* has a significantly negative coefficient; the coefficient on *OPI* for $\Delta Z\text{-}PROB_{[q-1;q+1]}$ is -0.544 (*t*-statistic = -6.28), and the coefficient on *OPI* for $\Delta Z\text{-}PROB_{[q-1;q+3]}$ is almost twice as large at -0.943 (*t*-statistic = -8.28). For an interquartile increase in *OPI* in each sample, these coefficients represent a decrease in *ΔZ-PROB* of 0.836 (= 1.536*-0.544) and 1.443 (=

1.530*-0.943), over the windows [*q*-1;*q*+1] and [*q*-1;*q*+3], respectively, which represent 9.5 to 11.8 times the sample mean or median of *ΔZ-PROB*. The next sets of columns present similar results for *ΔO-PROB* and even stronger results for *ΔBSM-PROB.* As we control for *FE* and $STOCKRET_{[-2;+2]}$, our findings are incremental to the association between *OPI* and earnings and announcement stock returns documented in Bartov et al. (2018). Overall, we find strong support that *OPI* potentially provides information related to future changes in default risk.

We next carry out cross-sectional tests to determine whether the association between *OPI* and changes in default risk is stronger in settings where *OPI* may have a more salient effect. We re-estimate Equation (4) using the same three partitions used before. Table 7, Panel B, focuses on subsamples of high and low proportion of bond/credit risk-related tweets. Interestingly, there is no difference between these two subsamples for any of the three credit risk measures, i.e., both bond/credit risk-related tweets and tweets related to firm fundamentals or securities trading are associated with future changes in default risk. This is an interesting contrast to our prior results, especially for our short-window tests, which were more pronounced for the high *%BOND* subsample. While *OPI* has a greater ability to predict announcement bond returns and changes in CDS spreads when *%BOND* is higher, the proportion of bond/credit risk-related tweets does not seem to have similar implications for the association between *OPI* and changes in default risk.

Table 7, Panel C, tests whether the association between *OPI* and *ΔPROB* may be more pronounced for speculative-grade bonds as opposed to investment-grade bonds. As the results indicate, *OPI* is significantly associated with *ΔPROB* in all specifications for both speculative-grade and investment-grade bonds. More importantly, we find that the coefficient on *OPI* is significantly larger in magnitude for speculative-grade bonds than investment-grade bonds for all the three measures of *ΔPROB*. For instance, in the regression where *ΔZ-PROB* is the dependent variable, the coefficient on *OPI* is -0.750 (*t*-statistic = -3.89) for speculative-grade bonds and -0.368 (*t*-statistic = -5.61) for investment-grade bonds, with the difference between these two coefficients, -0.382 being marginally significant (*t*-statistic = -1.87). We find stronger statistically significant differences in the *OPI* coefficients between speculative-grade bonds and investment-grade bonds for *ΔO-PROB* and *ΔBSM-PROB*, -0.382 (*t*-statistic = -2.13) and -2.218 (*t*-statistic = -5.20), respectively. These findings, which are consistent with the findings in Gkougkousi (2014) and Even-Tov (2017), suggest that Twitter provides information pertaining to future changes in default risk that is more relevant for firms with speculative-grade bonds.

Finally, Table 7, Panel D, estimates Equation (4) for the subsamples of high and low information uncertainty. Consistent with our conjecture, the association between *OPI* and *ΔPROB* is significantly more pronounced for the high information uncertainty subsample as opposed to the low information uncertainty subsample for all three alternative measures of changes in implied default probability. For example, when *ΔZ-PROB* is the dependent variable, the coefficient on *OPI* for the high uncertainty subsample, -0.942 (*t*-statistic = -5.04), is more than fourfold higher than the -0.215 (*t*-statistic = -3.60) coefficient on *OPI* for the low uncertainty subsample, and the difference between these two coefficients, -0.726, is highly significant (*t*-statistic = -3.70). This corroborates the evidence in Akins (2018) and suggests that the salience of information from Twitter for debt investors increases with information uncertainty. Overall, the results from Table 7 indicate the information *OPI* conveys to the bond market relates to changes in default risk.

Robustness and Additional Analyses

In addition to our primary vocabulary based *OPI* measure, we create an alternate measure, *OPI_BAYES*, based on the enhanced naïve Bayes algorithm developed by Narayanan et al. (2013). This algorithm identifies individual tweets as negative, positive, or neutral, and provides a probability level (between 50% and 100%) for reliability. To compute *OPI_BAYES*, we first weight each tweet by its probability and follow a similar process as we do for our primary *OPI* measure to aggregate individual tweets. Specifically, we weight each tweet by [1 + Log (1 + Number of Followers)]. Finally, *OPI_BAYES* is minus one multiplied by the weighted number of negative tweets, scaled by one plus the sum of the probability levels for positive and negative tweets. We rerun all the tests in the paper using *OPI_BAYES* as our metric of aggregate Twitter opinion. The results are qualitatively similar and tabulated in the first four tables of our Online Appendix (Tables OA1 to OA4).

Bartov et al. (2018) find that tweets conveying original information as well as tweets disseminating existing information predict upcoming earnings and announcement stock returns. Following their classification, we examine and find that the results (tabulated in the Online Appendix, Tables OA5 to OA8) also hold in our setting for both original tweets (50,937 tweets or 22% of our sample) as well as dissemination tweets (182,533 tweets or 78%). To provide examples, when estimating Equation (1) with *ΔCDSSPREAD* as the dependent variable, the *OPI* coefficients are significantly negative, -0.257 (*t*-statistic = -1.86) and -0.348 (*t*-statistic = -2.99), respectively, for original and dissemination tweets. Moreover, the difference between the two coefficients is statistically insignificant (*t*-statistic = -0.50). Likewise, when estimating Equation (4) with $\Delta BSM\text{-}PROB_{[q-1;q+1]}$ as the dependent variable, *OPI* exhibits significantly negative coefficients for original and dissemination tweets, -2.053 (*t*-statistic = -9.45) and -1.603 (*t*-statistic = -8.70), respectively, and the difference between the two coefficients is again statistically insignificant (*t*-statistic = 1.58). Thus, our findings hold for original tweets as well as dissemination tweets, suggesting that, like the stock market, Twitter also plays a dual role of communicating new information and disseminating existing information in the corporate bond market.

Prior research (e.g., Mao et al. 2012; Curtis et al. 2016) documents that social-media activity *per se* (i.e., number of messages) may be informative to investors. To confirm that aggregate Twitter opinion, not merely Twitter activity, underlies our findings, we test the sensitivity of our findings to the level of Twitter activity. To that end, we first partition our sample into two subsamples based on Twitter activity, measured as the number of tweets posted by individual investors during the *OPI* window, [-10;-3], and then we replicate our tests separately for each subsample. The results (tabulated in the Online Appendix, Tables OA9 to OA12) are robust. For instance, when estimating Equation (1) with *ΔCDSSPREAD* as the dependent variable, the *OPI* coefficients are significantly negative, -0.536 (*t*-statistic = -3.54) and -0.473 (*t*-statistic =

-2.28), respectively, for the high and low Twitter activity subsamples. Moreover, the difference in the coefficients between the two subsamples is not statistically significant (*t*-statistic = -0.25). Similarly, when estimating Equation (4) with $\Delta BSM\text{-}PROB_{[q\text{-}1;q+1]}$ as the dependent variable, *OPI* exhibits significantly negative coefficients for the high and low Twitter activity subsamples (-2.339 and -1.901, respectively, with *t*-statistics = -8.56 and -7.94), and the difference in the coefficients between the two subsamples is again statistically insignificant (*t*-statistic = -1.21). Thus, our findings are not driven by Twitter activity, but rather by the aggregate opinion derived from individual tweets.

VI. CONCLUSIONS

Prior research in accounting and finance examining the relevance and reliability of information from online and social media platforms for capital market participants focuses on the stock market. The goal of our study is to shine a light on the informational role of social media in the corporate bond market. For that purpose, we analyze the aggregate opinion of individual Twitter messages about firms and their prospects for a broad sample of Russell 3000 firms, focusing on tweets related to bonds, credit risk, and fundamental information.

Our first set of tests examines whether Twitter conveys economically important information to corporate bond market participants. We examine whether Twitter information helps predict bond returns and changes in CDS spreads around earnings announcements and whether Twitter information is associated with future changes in bond yield spreads. We find that aggregate Twitter opinion successfully predicts announcement bond returns and changes in CDS spreads and is negatively associated with future changes in bond yield spreads. These results hold after controlling for earnings news and announcement stock returns, and other controls, including the opinion from traditional media channels. Further, these associations are more pronounced when the underlying earnings news is negative, consistent with the nonlinear payoff structure of bonds.

Our second set of tests examines whether aggregate Twitter opinion is associated with future changes in credit ratings. We find that aggregate Twitter opinion is negatively associated with the probability of rating downgrades, but insignificantly related to the probability of upgrades. These results suggest that Twitter information reflects the information used by credit rating agencies, but only for credit rating downgrades. To better understand the nature of information conveyed by Twitter to the corporate bond market, our third and final set of tests examines whether aggregate Twitter opinion is associated with future changes in default risk. We document a significantly negative association between aggregate Twitter opinion and future changes in implied default probability. This association is more pronounced for firms with speculative-grade bonds and firms in more uncertain information environments. Thus, Twitter appears to provide a potentially relevant signal to bond market participants pertaining to default risk.

Overall, our findings suggest that aggregate Twitter opinion is potentially relevant and economically important, not only for stock market investors as documented by Bartov et al. (2018), but also for corporate bond market participants. We contribute to the literatures on the role of social media in capital markets and the role of earnings and financial disclosures in the corporate bond market. These two literatures have demonstrated, respectively, that Twitter information helps predict quarterly earnings and announcement stock-price changes (Bartov et al. 2018), and that the nonlinear payoff structure of bonds has important implications for the reaction of bond prices to earnings news (Easton et al. 2009). We contribute to these literatures by being the first to show that Twitter information predicts bond announcement returns and changes in CDS spreads and is associated with future changes in bond yield spreads and credit ratings, in a manner consistent with the nonlinear payoff structure of bonds. We also shed light on the nature of the information conveyed by aggregate Twitter opinion to the corporate bond market (i.e., changes in default risk). Notably, we provide novel evidence that social media appears to convey economically important information to even the presumably sophisticated investors who dominate the corporate bond market, an important financial market that differs significantly from the stock market, as well as to credit rating agencies. Our results may thus inform bond and CDS investors, bond analysts, and credit rating agencies.

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APPENDIX A: Variable Definitions

Variable	Definition
ANL	Natural logarithm of one plus the number of analysts in the latest I/B/E/S consensus analyst quarterly earnings per share (EPS) forecast prior to the quarter end date.
ASSETS	Total assets (*ATQ*).
BONDRET (%)	Buy-and-hold adjusted bond returns for the window specified, where day 0 is the quarterly earnings announcement date, multiplied by 100, using the Trace database. We exclude cancelled, corrected, commission, special trades and all trades under $100,000. We weight each of the remaining bond trades by dollar value to compute daily "clean" prices (prices before accrued interest) for each traded bond. We then add accrued interest to each clean price to calculate daily "dirty" prices (prices after accrued interest) for each traded bond, and compute daily raw bond returns using daily dirty prices. We adjust each daily raw return by subtracting the risk-free rate on that day, using the return on a Treasury security with similar maturity. We require the absolute value of the daily-adjusted bond returns to be less than 20% to eliminate erroneous data. We compute buy-and-hold adjusted bond returns for the window specified for each traded bond. Finally, if a firm has more than one traded bond in the quarter, we aggregate the individual buy-and-hold adjusted bond returns at the firm level using a value-weighted mean.
ΔBSM-PROB (%)	Change in implied default probability, multiplied by 100, where implied default probability is estimated based on the Black-Scholes-Merton model, as outlined in Hillegeist et al. (2004) and Bharath and Shumway (2008).[24] The default probability is estimated using the following standard normal distribution model: $$N\left(-\frac{\ln(V_A/X)+(\mu-(\sigma_A^2/2))}{\sigma_A}\right) \quad (5)$$ where V_A is market value of assets ((*CSHOQ***PRCCQ*)+*X*), *X* is face value of debt (*DLCQ*+0.5**DLTTQ*), μ is expected return on assets (measured using most recent V_A return), and σ_A is asset volatility (estimated iteratively using equity volatility and V_A return).
ΔCDSSPREAD (%)	Change in credit default swap (CDS) spread, for five-year CDS contracts denominated in U.S. dollars with MR type documentation and senior ('SNRFOR') tier, for the window specified, where day 0 is the quarterly earnings announcement date, computed as the CDS spread on the last day of the window divided by the CDS spread on the first day of the window minus one, multiplied by 100, using the Markit database.
ΔO-PROB (%)	Change in implied default probability, multiplied by 100, where implied default probability is estimated based on O-Score converted into probability using the logit function and O-Score is computed using Ohlson's (1980) model as follows: O = -1.32 - 0.407*Log(*ATQ**1,000,000/GNPIndex) + 6.03*(*LTQ*/*ATQ*) - 1.43*(*ACTQ-LCTQ*)/*ATQ* + 0.0757*(*LCTQ*/*ACTQ*) - 2.37**X* - 1.83*(*NIQ*/*ATQ*) - 1.72*(4*(*PIQ+DPQ*))/*LTQ* + 0.285**Y* - 0.521*(*NIQ* - *LNIQ*)/ ((abs(*NIQ*)+abs(*LNIQ*)) (6) where *X*=1 if *LTQ*>*ATQ*, 0 otherwise, and *Y*=1 if *NIQ*<0 and *LNIQ*<0, 0 otherwise.
ΔRATING	Categorical variable equal to minus one if a traded bond has a decrease in S&P rating (i.e., downgrade), equal to plus one if a traded bond has an increase in S&P rating (i.e., upgrade), zero otherwise, using the Mergent FISD database.
ΔYIELD	Change in bond yield spread, where bond yield spread is the difference between the yield to maturity of a traded bond and the yield to maturity of a Treasury security with a corresponding duration, using the Trace database. If a firm has more than one traded bond, we calculate the weighted average yield spread of the individual bonds. The yields on Treasury securities are from the H.15 release published by the Federal Reserve Bank of New York.
ΔZ-PROB (%)	Change in implied default probability, multiplied by 100, where implied default probability is estimated based on Z-Score converted into probability using the logit function and Z-Score is computed using Altman's (1968) model as follows: Z = 1.2*(*ACTQ-LCTQ*)/*ATQ* + 1.4*(*REQ*/*ATQ*) + 3.3*(4**NIQ-XINTQ-TXTQ*)/*ATQ* + 0.6*(*PRCCQ***CSHOQ*)/*LTQ* + 0.999*(4**SALEQ*/*ATQ*) (7)

[24] Additional details are available in the Appendix of Hillegeist et al. (2004).

DOWNGRADE	Indicator variable equal to one if a traded bond has a decrease in S&P rating, zero otherwise, using the Mergent FISD database.
FE (%)	Analyst earnings forecast error, measured as I/B/E/S reported quarterly EPS less the latest I/B/E/S consensus analyst quarterly EPS forecast just prior to the quarterly earnings announcement date, scaled by stock price as of the forecast date, multiplied by 100.
HORIZON	Number of days between the quarterly earnings announcement date and the traded bond's maturity date, using the Mergent FISD database. If a firm has more than one traded bond, we aggregate the individual bond horizons at the firm level using a value-weighted mean.
INST	Number of shares held by institutional investors scaled by total shares outstanding as of the quarter end date, using the Thomson-Reuters 13F database.
LEV	Total (short-term and long-term) debt scaled by total assets (*DLTTQ*+*DLCQ*)/*ATQ*).
LOSS	Indicator variable equal to one if earnings before extraordinary items (*IBQ*) is strictly negative in the quarter, zero otherwise.
MB	Ratio of market value to book value of equity ([*CSHOQ***PRCCQ*]/*CEQQ*) as of the quarter end date.
MVE	Market value of equity (*CSHOQ***PRCCQ*).
OPI	Single factor from a factor analysis using three vocabulary-based measures. The number of words classified as negative in each tweet is weighted by the number of followers of the user {1 + [Log(1 + Number of Followers)]}. Each measure is defined as minus one multiplied by the sum of the weighted number of negative words during the eight-trading-day window [-10;-3], where day 0 is the quarterly earnings announcement date, scaled by one plus the number of words classified as positive or negative. The three measures employ, respectively, the following word lists and exclude words with negations: the Loughran and McDonald (2011) word list, the Harvard Psychosociological Dictionary (i.e., Harvard IV-4 TagNeg H4N) word list, and the Hu and Liu (2004) word list.
%BOND	Proportion of bond and/or credit risk-related tweets, measured as the percentage of tweets with bond and/or credit risk-related words and phrases.
Q4	Indicator variable equal to one if the quarter is the fourth fiscal quarter, zero otherwise.
RATING	S&P rating converted as AAA=1, AA+=2, …, D=22, using the Mergent FISD database. If a firm has more than one traded bond in the quarter, we calculate the weighted average S&P rating of the individual bonds.
ROA	Net income before extraordinary items (*IBQ*) scaled by average total assets (*ATQ*).
RP_OPI	Minus one multiplied by the number of traditional news events classified as negative during the eight-trading-day window [-10;-3], where day 0 is the quarterly earnings announcement date, using the RavenPack database. Each traditional news event is weighted by RavenPack's ESS (Event Sentiment Score) rescaled to range between 0 and 1, where higher values indicate stronger sentiment. The measure is scaled by one plus the sum of the ESS rescaled for positive or negative traditional news events.
SIZE	Natural logarithm of *MVE* as of the quarter end date.
SPEC	Indicator variable equal to one for traded bonds with S&P rating below BBB-, zero otherwise, using the Mergent FISD database. If a firm has more than one traded bond in the quarter, we use the weighted average rating of individual bonds.
STOCK RETURN VOLATILITY	Stock return volatility, measured as the standard deviation of daily stock returns over the calendar year prior to the quarterly earnings announcement date, using the CRSP daily database.
STOCKRET (%)	Using Carhart's (1997) four-factor model, we measure the buy-and-hold abnormal returns for firm *i* over the trading days around the quarterly earnings announcement date (day 0), as: $$STOCKRET = \prod (1 + R_{it}) - \prod (1 + ER_{it}) \quad (8)$$ where, R_{it} is the daily return for firm i on day t, inclusive of dividends and other distributions, and ER_{it} is the expected return on day t for that firm. Returns are multiplied by 100. If a firm delists during the return accumulation window, we compute the remaining return by using the CRSP daily delisting return, reinvesting any remaining proceeds in the appropriate benchmark portfolio, and adjusting the corresponding market return to reflect the effect of the delisting return on our measures of expected returns. Following Shumway (1997), we set missing performance-related delisting returns to -100%. We compute the daily abnormal returns using Carhart's (1997) four-factor model by first estimating the following model using a 40-trading-day hold-out period, starting 55 trading days prior to the earnings announcement date:

	$R_{it} - RF_t = a_i + b_i(RMRF_t) + s_i(SMB_t) + h_i(HML_t) + p_i(UMD_t) + e_{it}$ (9) where, R_{it} is defined as before, RF_t is the one-month T-bill daily return, $RMRF_t$ is the daily excess return on a value-weighted aggregate stock market proxy, SMB_t is the size factor, HML_t is the book-to-market factor, and UMD_t is the momentum factor. We use the estimated slopes from Equation (9), b_i, s_i, h_i, and p_i, to compute the expected return for firm *i* on day *t* as follows: $ER_{it} = RF_t + b_i(RMRF_t) + s_i(SMB_t) + h_i(HML_t) + p_i(UMD_t)$ (10) *RF*, *RMRF*, *SMB*, *HML*, and *UMD* are obtained from Professor Kenneth French's web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, accessed March 15, 2022).
SUBORD	Indicator variable equal to one if the firm has at least one traded bond in the quarter that is subordinated (identified as security_level other than 'SEN' or 'SS' in the Mergent FISD database, zero otherwise.
UPGRADE	Indicator variable equal to one if a traded bond has an increase in S&P rating, zero otherwise, using the Mergent FISD database.

APPENDIX B: Selecting Individual Tweets

We select individual tweets containing bond-, credit risk-, fundamentals-, and/or securities trading-related words and phrases. The list of bond- and/or credit risk-related words and phrases is compiled using the credit risk dictionary in Sethuraman (2019) augmented with additional words and phrases inspired from Campbell et al. (2014). It includes the following words and phrases:

acquisition, additional capital, additional financing, adverse effect, adverse impact, agreement, amend, amendment, anti-takeover provision, anti-takeover provisions, asset sale, asset sales, assurance, assure, bad debt, balance, bank, bank borrowing, bank debt, bankrupt, bankruptcy, base, bond, bondholder, borrow, borrowing, borrowing base, borrowing capacity, callable, capital, capital deficiency, capital expenditure, capital expenditures, capital lease, capital leases, carryforward, cash need, cash, cdo, cds, cease, ceased, chapter 11, chapter 7, claim, close, closure, collateral, collection, commitment, competition, competitor, concentrated ownership, concern, contingency, contract, contractual obligation, covenant, convertible, coupon, covenant, covenants, coverage, coverage ratio, credit, credit facilities, credit facility, credit line, credit rating, credit risk, creditworthiness, curve, debt, debt agreement, debt balance, debt burden, debt covenant, debt discount, debt expense, debt financing, debt level, debt obligation, debt repayment, debt service, decline in price, decline in stock price, decline, deem, default, default provision, deficit, defined benefit, delay, derivative, difficulty, dilution, discontinue, discontinue operation, discontinued, disposal, disposal activity, disposition, disruption, dividends, doubt, downgrade, drop, duration, elimination, event, exit, expenditure, expense, face value, facilities, facility, fail, failure, family, file, filing, finance, financial, financial condition, financial covenant, financing, financing arrangement, financing costs, fitch, flow, force, foreclose, funded status, future, going, going concern, grade, growth, holder, illiquid market, immediately, impact, impairment, improvements, inability, incur, indebted, indebtedness, indenture, inflation, insider sales, insider, insurance, interest, interest payment, invest, investment, issuance, issuance cost, issue, junior, junk, lack, late, lawsuit, lease, lease commitment, lease commitments, lease obligation, leasehold, leases, leasing, legal, lender, leverage, leverage ratio, leveraged lease, leveraged leases, liability, libor, lien, likely to, limitation, limited trading, liquid, liquidation, liquidity, liquidity need, liquidity position, listing, litigation, loan, loan agreement, locked-in lease, locked-in leases, long-term debt, loss, mandatory contribution, market risk, material impact, maturity, mbs, meet, merger, modification, moody, mortgage, negative cash , negative operating cash flow , negotiate, negotiation, net loss, new credit, new financing, note, notes, o.p.e.b., obligation, obligations, offering, opeb, operating loss, operating losses, outstanding, ownership, payable, payment, penalty, penny stock, penny, pension, poors, postretirement, prepayment, pressure, prime, prime rate, principal, proceed, proceeds, profitability, protection, raise, rate, rate risk, rating, recoverability, redeem, reduction, refinance, refinancing, reinsurance, renegotiation, reorganization, reorganize, repay, repayment, reserve, reserves, restatement, restriction, restructure, restructuring, result, retire, reversal, revolver, revolving, revolving credit, risk factor, risk, sale, schedule, secondary, secure, secured, securities, security, seek, sell asset, senior, settle, settlement, severance, severe, severity, speculative, spread, strategy, strong, structure, subject to, subordinate, subordinated, substantial, substantial doubt, success, sufficient, sufficient cash, swap, term, terminate, termination, unable, underfunded pensions, underwriting, unless, upgrade, valuation, variable rate, vendor, violation, volatility, warrant, workforce reduction, working cap, working capital, worth, write, write down, write off, writedown , write-down , writeoff , write-off , yield

The list of fundamentals-related words and phrases is based on the list compiled by Bartov et al. (2018) and includes the following:

accounting, acquir, adjusted, aggressive, asset, balance sheet, boosted, business model, capacity, capital, cash, CDS, charge, compete, competit, conservative, consumer, contract, corporat, covenant, customer, debt, decline, demand, dividend, earning, ebit, ebitda, effective, eps, equity, executive, expense, financial statement, fiscal, forecast, fraud, gaap, gain, goodwill, growth, in the black, in the green, in the red, income, income statement, industry, inflate, innovati, internal control, inventory, investigat, lawsuit, legal, lever, liquidity, loss, m&a, margin, miss, noi, nopat, normalized, obfuscate, oibda, operating, overstat, patent, peer, per share, ponzi, pro forma, pro-forma, produc, profit, proforma, pyramid, rating, red flag, reserv, resource, restructur, results, revenue, risk, roll-up, sales, solven, supplier, surprise, takeover, technolog, whisper, writedown, write-down, writeoff, write-off, yearend, year-end.

The list of securities trading-related words and phrases is based on the list compiled by Bartov et al. (2018) and includes the following:

after hour, analyst, bear, bought, break, bull, buy, call, climb, close, cover, downgrade, downside, halt, high, invest, long, low, market, move, moving, open, play, position, price, put, quote, rally, resistance, sell, share, short, sold, spike, stock, stop, support, target, trade, trading, tumble, upgrade, upside, valuation, value, volume.

APPENDIX C: Examples of Individual Tweets

Date	Ticker	Tweet	Username	Followers
04/19/2009	BAC	$bac raises cc rates on ppl under 10 pct -they are getting ppl who can pay down to do it. Bad debt=% of cc rec. =less writeoffs butno1cares	bnkr0	0
04/08/2010	MEE	$mee , explosion wont affect rating, says moodys	Jamielissette	0
07/15/2010	APA	$APA getting BP Alaska assets on the cheap at about 2.2x cash flow, but doubling leverage in the process.	AJInsight	0
02/02/2011	EQIX	Looking at $EQIX // very interesting...too much debt accumulated too soon...will look into this...but not before earnings!	Princebhojwani	45
11/08/2011	DYN	$DYN Restructuring Agreement with Holders of Over $1.4B Of Sr Notes; 4 Subsidiaries File for Relief Under Chapter 11	Benziga	26,437
01/25/2012	GTIV	Gentiva Health Services, Inc. was rated High Risk. #Stocks #Risk $GTIV #Healthcare	Direports	332
02/08/2012	FTR	Frontier Communications is mired in #fraud & on its way to zero. Grab puts before this POS is filing for bankruptcy. $FTR #options #FCC	Pellucidigm	244
02/24/2012	DYN	RT @bman_microcaps: $DYN bottom play inching **Yeah..but bankruptcy?	Urbane_Gorilla	2,472
04/16/2012	CSCO	@jimiuorio damn straight, $CSCO is going bankrupt	trader_74	0
04/30/2012	DYN	Carlyle Group hedge fund fights to derail Dynegy bankruptcy settlement http://t.co/GeWJQJG6 $DYN	Amyposzywak	64
05/03/2012	AONE	@SamSntar want to take a peek at balance sheet of $AONE given the losses and WRITEOFFS and missing cash coming??	wind4me	5,957
08/01/2012	ANR	$ANR Chapter 11 comin??? Staying away from this knife for now	KrustyLovesYou	7
08/01/2012	NLY	@MicroFundy also appreciate the fact that $NLY seems to understand current risks and are maintaining leverage at low end of their typ. Range	templec4	2,673

APPENDIX D: Measuring and Aggregating Opinion from Individual Tweets

Commercial Metals Company (CMC), Quarterly earnings announcement date: January 6, 2012

10 tweets in our sample mentioning $CMC between December 22, 2011 and January 3, 2012

#	Tweet	Followers
1	$CMC http://t.co/YCtIhX5t Long setup to watch	9,160
2	@DMAugustine Yes, but couldn't get going today $CMC	3,581
3	$CMC Icahn Sends Letter; Says Will Drop Proxy if 40.1% of Shares Not Tendered	26,730
4	Icahn vows to continue fight for Commercial Metals if he receives 40.1% of shares in tender offer. http://t.co/wY4d2aqT $CMC #mna #stocks	2,753
5	$CMC last price 13.93 below SMA20 and S2 on 6.65x relative volume (ATR: 0.48)	34
6	$CMC Announces an Amended Five-Year Credit Agreement and an Amended Receivables Purchase Agreement	26,807
7	RT @Benzinga: $CMC Announces an Amended Five-Year Credit Agreement and an Amended Receivables Purchase Agreement	2,028
8	$CMC Commercial Metals Company Announces an Amended Five-Year Credit... http://t.co/g9DfQPzb	174
9	$CMC Commercial Metals Company Sends Letter to Stockholders http://t.co/nYX3Mjbf	173
10	SCALPSWINGSTRADDLE: THE_YAK: $CMC says Icahn's offer too low, urges shareholders http://t.co/X7839RzC	69

#	Number of Negative / Positive Words					
	Loughran and McDonald		Harvard IV-4		Hu and Liu	
	OPI_A		*OPI_B*		*OPI_C*	
	Neg.	Pos.	Neg.	Pos.	Neg.	Pos.
1	0	0	0	0	0	0
2	0	0	1	0	0	0
3	0	0	1	0	0	0
4	0	0	1	1	0	1
5	0	0	0	0	0	0
6	0	0	0	3	0	0
7	0	0	0	3	0	0
8	0	0	0	2	0	0
9	0	0	0	1	0	0
10	0	0	2	1	0	0

OPI_A = 0

OPI_B = -1 * (1*{1+[Log(1+3581)]} + 1*{1+[Log(1+26730)]} + 1*{1+[Log(1+2753]} + 2*{1+[Log(1+69)]}) / (1+5+11) = -2.341

OPI_C = 0

OPI = single factor using *OPI_A*, *OPI_B*, *OPI_C* = -0.780

APPENDIX D (cont'd)

<u>Charles Schwab Corporation (SCHW), Quarterly earnings announcement date: January 18, 2011</u>

10 tweets in our sample mentioning $SCHW between January 3, 2011 and January 12, 2011

#	Tweet	Followers
1	Charles Schwab $SCHW Broke Resistance http://wibi.us/dNBs5i	170
2	Just installed $SCHW iPhone app. No live updating of quotes or PnL, trade entry only marginally easier than mobile browser. Good start $$	320
3	Schwab $SCHW to pay more than $118M to settle SEC suit	3,756
4	Schwab (SCHW) Statement on Resolution Related to the YieldPlus Fund ... $schw ... http://tinyurl.com/2dvzh5j	705
5	Schwab Agrees to Pay $119 Million to Settle SEC Claims http://bit.ly/eOrZ5g $SCHW	27,737
6	BloombergNow Schwab Agrees to Pay $119 Million to Settle SEC Claims http://bit.ly/eOrZ5g $SCHW	3,180
7	RT @BloombergNow: Schwab Agrees to Pay $119 Million to Settle SEC Claims http://bit.ly/eOrZ5g $SCHW	36,937
8	RT @BloombergNow: Schwab Agrees to Pay $119 Million to Settle SEC Claims http://bit.ly/eOrZ5g $SCHW	343
9	SEC settles with $SCHW for $119M for misleading investors & failing to prevent the misuse of nonpublic information	408
10	$SCHW http://chart.ly/6wa4ehl Retail investor is back? Watch for a break of 18.25	500

#	Number of Negative / Positive Words					
	Loughran and McDonald		Harvard IV-4		Hu and Liu	
	OPI_A		*OPI_B*		*OPI_C*	
	Neg.	Pos.	Neg.	Pos.	Neg.	Pos.
1	0	0	1	0	2	0
2	0	2	0	2	1	2
3	0	0	0	3	0	0
4	0	0	0	0	0	0
5	1	0	0	2	0	0
6	1	0	0	2	0	0
7	1	0	0	2	0	0
8	1	0	0	2	0	0
9	3	0	1	0	3	0
10	1	0	1	1	1	0

OPI_A = -1 * (1*{1+[Log(1+27737)]} + 1*{1+[Log(1+3180)]} + 1*{1+[Log(1+36937]}
+ 1*{1+[Log(1+343)]} + 3*{1+[Log(1+408)]} + 1*{1+[Log(1+500)]}) / (1+8+2) = -6.083

OPI_B = -1 * (1*{1+[Log(1+170)]} + 3*{1+[Log(1+408)]} + 1*{1+[Log(1+500)]}) / (1+3+14) = -1.132

OPI_C = -1 * (2*{1+[Log(1+170)]} + 1*{1+[Log(1+320)]} + 3*{1+[Log(1+408]}
+ 1*{1+[Log(1+500)]}) / (1+7+2) = -4.731

OPI = single factor using *OPI_A*, *OPI_B*, *OPI_C* = -3.982

TABLE 1

Sample Selection

Criterion	Tweets	Firm-Quarter Observations	Unique Firms
Tweets between March 21, 2006 and December 31, 2012 with $ tag followed by ticker symbols of Russell 3000 firms	10,894,037	66,290	4,733
Tweets pertaining to a single stock symbol	8,713,182	61,357	4,668
Availability of data on the Compustat database	8,674,195	60,638	4,596
Tweets on or after December 17, 2008 (i.e., ten trading days prior to January 1, 2009)	8,462,761	54,906	4,132
Firms with traded bonds and bond return data using the Trace database	3,139,188	9,717	1,193
Tweets pertaining to a ticker symbol with no generic meaning[a]	2,692,185	9,404	1,158
Tweets mentioning bond-, credit risk-, fundamentals-, and/or securities trading-related words and phrases[b]	2,159,448	9,347	1,158
Tweets in the trading-day window [-10;-3][c]	232,930	7,356	1,037
Final Sample	**232,930**	**7,356**	**1,037**

[a] The complete list of ticker symbols with generic meaning is: $A, $AH, $AI, $AIR, $ALE, $AM, $AME, $AN, $AP, $B, $BC, $BIG, $C, $CAM, $CASH, $CDS, $D, $DOW, $DV, $EE, $EF, $EL, $END, $FOR, $G, $GDP, $H, $HA, $HAE, $HAR, $HE, $HITT, $HOME, $HOT, $HT, $IM, $IN, $IR, $K, $L, $LIFE, $LOW, $M, $MALL, $MAN, $MTG, $NEWS, $O, $OME, $OMG, $P, $QUAD, $R, $RT, $SIX, $UA, $WAG, $WIN, $X, $Y.

[b] See Appendix B for the list of bond-, credit risk-, fundamentals-, and/or securities trading-related words and phrases.

[c] Day 0 is the quarterly earnings announcement date, and quarterly earnings announcement dates are between January 1, 2009 and December 31, 2012.

TABLE 2
Sample Distribution

Panel A: Distribution by Calendar Quarter

Calendar Quarter	Tweets		Bond-Quarters		Firm-Quarters	
	N	%	N	%	N	%
2009, Jan-Mar	673	0.29	837	2.86	146	1.99
2009, Apr-Jun	2,746	1.18	1,258	4.29	265	3.60
2009, Jul-Sept	3,412	1.46	1,434	4.90	321	4.36
2009, Oct-Dec	3,629	1.56	1,470	5.02	316	4.30
2010, Jan-Mar	5,232	2.25	1,813	6.19	423	5.75
2010, Apr-Jun	5,594	2.40	1,816	6.20	438	5.96
2010, Jul-Sept	6,361	2.73	1,789	6.11	465	6.32
2010, Oct-Dec	5,962	2.56	1,879	6.42	462	6.28
2011, Jan-Mar	17,300	7.43	2,167	7.40	574	7.80
2011, Apr-Jun	15,950	6.85	2,118	7.23	583	7.93
2011, Jul-Sept	20,164	8.66	1,972	6.73	526	7.15
2011, Oct-Dec	27,658	11.87	2,065	7.05	540	7.34
2012, Jan-Mar	28,552	12.26	2,175	7.43	567	7.71
2012, Apr-Jun	40,551	17.41	2,125	7.25	557	7.57
2012, Jul-Sept	23,773	10.20	2,112	7.21	563	7.65
2012, Oct-Dec	25,373	10.89	2,257	7.71	610	8.29
All	**232,930**	**100.00**	**29,287**	**100.00**	**7,356**	**100.00**

TABLE 2 (continued)
Panel B: Distribution by Industry based on Fama-French 48-Industry Classification

Industry Group & Description	Tweets		Bond-Quarters		Firm-Quarters		Compustat
	N	%	N	%	N	%	%
1: Agriculture	404	0.17	29	0.10	25	0.34	0.38
2: Food Products	2,872	1.23	440	1.50	174	2.37	1.34
3: Candy and Soda	480	0.21	123	0.42	33	0.45	0.33
4: Alcoholic Beverages	1,922	0.82	407	1.39	65	0.88	0.27
5: Tobacco Products	759	0.33	234	0.80	32	0.43	0.10
6: Recreational Products	365	0.16	28	0.10	17	0.23	0.57
7: Entertainment	7,773	3.34	202	0.69	121	1.64	1.25
8: Printing and Publishing	671	0.29	77	0.26	47	0.64	0.47
9: Consumer Goods	2,277	0.98	300	1.02	80	1.09	1.05
10: Apparel	589	0.25	55	0.19	47	0.64	0.95
11: Healthcare	1,901	0.82	268	0.92	154	2.09	1.30
12: Medical Equipment	2,584	1.11	339	1.16	147	2.00	2.82
13: Pharmaceutical Products	12,826	5.51	1,133	3.87	361	4.91	6.86
14: Chemicals	3,293	1.41	426	1.46	179	2.43	1.79
15: Rubber and Plastic Products	78	0.03	31	0.11	16	0.22	0.49
16: Textiles	135	0.06	30	0.10	19	0.26	0.19
17: Construction Materials	1,491	0.64	194	0.66	99	1.35	1.23
18: Construction	2,081	0.89	220	0.75	119	1.62	0.84
19: Steel Works, Etc.	3,185	1.37	364	1.24	111	1.51	1.08
20: Fabricated Products	8	0	1	0.00	1	0.01	0.16
21: Machinery	4,057	1.74	728	2.49	131	1.78	2.38
22: Electrical Equipment	857	0.37	108	0.37	67	0.91	1.46
23: Automobiles and Trucks	3,859	1.66	371	1.27	102	1.39	1.30
24: Aircraft	2,215	0.95	459	1.57	79	1.07	0.41
25: Shipbuilding, Railroad Equipment	165	0.07	20	0.07	18	0.24	0.16
26: Defense	526	0.23	97	0.33	32	0.43	0.16
27: Precious Metals	586	0.25	79	0.27	21	0.29	1.55
28: Non-Metallic and Metal Mining	2,517	1.08	126	0.43	53	0.72	1.69
29: Coal	4,189	1.8	190	0.65	90	1.22	0.33
30: Petroleum and Natural Gas	19,962	8.57	2,092	7.14	672	9.13	4.85
31: Utilities	8,003	3.44	1,805	6.16	422	5.74	3.94
32: Communications	9,848	4.23	2,049	7.00	301	4.09	3.19
33: Personal Services	1,023	0.44	155	0.53	63	0.86	1.00
34: Business Services	27,498	11.80	1,026	3.50	379	5.15	9.97
35: Computers	11,362	4.88	781	2.67	194	2.64	2.79
36: Electronic Equipment	9,735	4.18	612	2.09	341	4.64	5.51
37: Measuring and Control Equipt	1,091	0.47	121	0.41	78	1.06	1.57
38: Business Supplies	2,377	1.02	337	1.15	148	2.01	0.83
39: Shipping Containers	424	0.18	80	0.27	38	0.52	0.20
40: Transportation	4,451	1.91	589	2.01	201	2.73	2.73
41: Wholesale	1,752	0.75	212	0.72	152	2.07	2.69
42: Retail	12,910	5.54	1,354	4.62	354	4.81	3.45
43: Restaurants, Hotels, Motels	4,841	2.08	232	0.79	79	1.07	1.31
44: Banking	21,804	9.36	4,619	15.77	417	5.67	10.64
45: Insurance	10,005	4.29	2,280	7.79	465	6.32	2.76
46: Real Estate	415	0.18	40	0.14	21	0.29	1.06
47: Trading	16,245	6.97	2,397	8.18	500	6.80	6.23
48: Miscellaneous	4,519	1.94	1,427	4.87	91	1.24	2.37
All Industries	**232,930**	**100.00**	**29,287**	**100.00**	**7,356**	**100.00**	**100.00**

The sample consists of 232,930 tweets (16,947 distinct users) covering 29,287 bond-quarter observations and 7,356 firm-quarter observations (1,037 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012.

TABLE 3
Descriptive Statistics and Correlation Matrix

Panel A: Descriptive Statistics

Variable	P1	Q1	Mean	Median	Q3	P99	Std. Dev.
OPI	-2.695	-0.695	0.005	0.467	0.803	0.945	0.985
$BONDRET_{[-2;+2]}$ (%)	-6.308	-0.369	0.118	0.074	0.562	6.602	1.647
$\Delta CDSSPREAD_{[-2;+2]}$ (%)	-22.799	-3.560	-0.412	-0.278	1.979	28.727	7.461
$\Delta YIELD_{[q-1;q+1]}$	-14.093	-1.072	-0.173	-0.230	0.401	19.472	3.550
$\Delta YIELD_{[q-1;q+3]}$	-15.319	-1.175	-0.095	-0.248	0.381	26.939	4.509
$DOWNGRADE_{[-2;+65]}$	0.000	0.000	0.046	0.000	0.000	1.000	0.211
$DOWNGRADE_{[-2;+190]}$	0.000	0.000	0.103	0.000	0.000	1.000	0.304
$UPGRADE_{[-2;+65]}$	0.000	0.000	0.040	0.000	0.000	1.000	0.197
$UPGRADE_{[-2;+190]}$	0.000	0.000	0.103	0.000	0.000	1.000	0.304
$\Delta Z\text{-}PROB_{[q-1;q+1]}$ (%)	-30.500	-1.810	-0.052	-0.069	1.442	31.883	7.042
$\Delta Z\text{-}PROB_{[q-1;q+3]}$ (%)	-32.219	-2.034	-0.115	-0.125	1.423	34.510	7.579
$\Delta O\text{-}PROB_{[q-1;q+1]}$ (%)	-23.177	-0.234	0.037	0.001	0.266	26.901	4.623
$\Delta O\text{-}PROB_{[q-1;q+3]}$ (%)	-23.669	-0.217	0.003	-0.001	0.240	26.143	4.484
$\Delta BSM\text{-}PROB_{[q-1;q+1]}$ (%)	-65.717	-0.050	-2.140	0.000	0.000	51.622	14.228
$\Delta BSM\text{-}PROB_{[q-1;q+3]}$ (%)	-86.609	-0.194	-3.796	0.000	0.000	61.681	19.067
FE (%)	-7.143	-0.052	0.014	0.070	0.259	3.597	1.124
$STOCKRET_{[-2;+2]}$ (%)	-23.553	-3.760	-0.125	-0.098	3.632	22.619	7.318
$STOCKRET_{[-10;-3]}$ (%)	-15.563	-2.270	0.283	0.277	2.761	17.640	5.149
RP_OPI	-0.757	-0.230	-0.135	0.000	0.000	0.000	0.187
LEV	0.000	0.163	0.288	0.272	0.396	0.755	0.177
ROA	-0.098	0.002	0.008	0.009	0.018	0.061	0.021
ASSETS	453	3,771	40,978	9,817	29,534	830,412	111,025
MVE	157	2,141	17,596	6,351	16,970	185,828	32,348
SIZE	5.057	7.669	8.703	8.756	9.739	12.133	1.527
MB	0.293	1.156	2.837	1.802	2.945	29.814	3.851
ANL	0.000	2.197	2.475	2.708	2.996	3.584	0.813
INST	0.000	0.645	0.725	0.786	0.897	1.000	0.252
Q4	0.000	0.000	0.236	0.000	0.000	1.000	0.424
LOSS	0.000	0.000	0.197	0.000	0.000	1.000	0.398
HORIZON	296	1,643	3,165	2,494	3,990	10,934	2,263
RATING	1.866	7.237	10.847	10.000	13.501	23.000	4.925
SPEC	0.000	0.000	0.435	0.000	1.000	1.000	0.496
SUBORD	0.000	0.000	0.163	0.000	0.000	1.000	0.369

TABLE 3 (continued)

Panel B: Correlation Matrix *OPI* and Dependent Variables

	OPI	*BOND RET* $_{[-2;+2]}$	*ΔCDS SPREAD* $_{[-2;+2]}$	*ΔYIELD* $_{[q-1;q+1]}$	*ΔYIELD* $_{[q-1;q+3]}$	*DOWN GRADE* $_{[-2;+65]}$	*DOWN GRADE* $_{[-2;+190]}$	*UP GRADE* $_{[-2;+65]}$	*UP GRADE* $_{[-2;+190]}$	*ΔZ-PROB* $_{[q-1;q+1]}$	*ΔZ-PROB* $_{[q-1;q+3]}$	*ΔO-PROB* $_{[q-1;q+1]}$	*ΔO-PROB* $_{[q-1;q+3]}$	*ΔBSM-PROB* $_{[q-1;q+1]}$	*ΔBSM-PROB* $_{[q-1;q+3]}$
OPI		0.05***	-0.07***	-0.12***	-0.20***	-0.03**	-0.04***	-0.01	0.02*	-0.10***	-0.16***	-0.06***	-0.13***	-0.21***	-0.25***
BONDRET$_{[-2;+2]}$	0.05***		-0.34***	-0.11***	-0.13***	-0.03***	-0.05***	0.01	0.02*	-0.10***	-0.10***	-0.04***	-0.06***	-0.05***	-0.09***
ΔCDSSPREAD$_{[-2;+2]}$	-0.07***	-0.34***		0.14***	0.13***	0.05***	0.04***	-0.01	-0.03	0.11***	0.12***	0.08***	0.05**	0.08***	0.08***
ΔYIELD$_{[q-1;q+1]}$	-0.08***	-0.08***	0.12***		0.56***	0.05***	0.07***	-0.04***	-0.03**	0.17***	0.20***	0.06***	0.11***	0.40***	0.39***
ΔYIELD$_{[q-1;q+3]}$	-0.10***	-0.05***	0.11***	0.55***		0.01	0.07***	-0.03**	-0.05***	0.15***	0.23***	0.07***	0.14***	0.25***	0.45***
DOWNGRADE$_{[-2;+65]}$	-0.03***	-0.04***	0.07***	0.05***	-0.01		0.62***	-0.05***	-0.07***	0.06***	0.07***	0.07***	0.08***	0.07***	0.02
DOWNGRADE$_{[-2;+190]}$	-0.05***	-0.05***	0.06***	0.05***	0.01***	0.62***		-0.07***	-0.11***	0.05***	0.12***	0.06***	0.10***	0.06***	0.03***
UPGRADE$_{[-2;+65]}$	-0.01	0.01	-0.01	-0.03**	-0.02*	-0.05***	-0.07***		0.59***	0.01	0.00	0.02*	0.01	-0.01	0.02*
UPGRADE$_{[-2;+190]}$	0.02	0.02*	-0.03*	-0.02	-0.02	-0.07***	-0.11***	0.59***		-0.05***	-0.06***	-0.02	-0.04***	-0.03**	0.00
ΔZ-PROB$_{[q-1;q+1]}$	-0.09***	-0.10***	0.08***	0.15***	0.10***	0.08***	0.05***	0.02	-0.03**		0.55***	0.63***	0.34***	0.32***	0.27***
ΔZ-PROB $_{[q-1;q+3]}$	-0.13***	-0.10***	0.09***	0.16***	0.15***	0.09***	0.12***	0.01	-0.03**	0.62***		0.30***	0.58***	0.32***	0.40***
ΔO-PROB $_{[q-1;q+1]}$	-0.04***	-0.06***	0.06***	0.11***	0.08***	0.07***	0.05***	0.00	-0.02	0.69***	0.40***		0.44***	0.10***	0.12***
ΔO-PROB $_{[q-1;q+3]}$	-0.07***	-0.06***	0.03	0.11***	0.15***	0.07***	0.09***	0.00	-0.02	0.42***	0.66***	0.51***		0.17***	0.21***
ΔBSM-PROB$_{[q-1;q+1]}$	-0.16***	-0.09***	0.09***	0.32***	0.23***	0.08***	0.06***	-0.01	-0.04***	0.22***	0.24***	0.12***	0.14***		0.64***
ΔBSM-PROB$_{[q-1;q+3]}$	-0.17***	-0.15***	0.13***	0.34***	0.34***	0.00	0.01	0.00	-0.01	0.23***	0.30***	0.15***	0.21***	0.76***	

TABLE 3 (continued)

Panel C: Correlation Matrix *OPI* and Independent Variables

	OPI	*FE*	*STOCK RET* [-2;+2]	*STOCK RET* [-10;-3]	*RP OPI*	*LEV*	*ROA*	*SIZE*	*MB*	*ANL*	*INST*	*Q4*	*LOSS*	*HORI ZON*	*RAT ING*	*SPEC*	*SUB ORD*
OPI		0.06***	0.03***	0.01	0.13***	0.03***	-0.06***	-0.23***	-0.10***	-0.24***	0.02**	-0.01	0.06***	-0.01	0.11***	0.08***	0.04***
FE	0.01		0.33***	0.06***	0.02	-0.02	0.19***	0.01	-0.03***	0.01	0.04***	-0.03***	-0.05***	0.03**	0.00	-0.01	0.05***
STOCKRET$_{[-2;+2}$	0.04***	0.24***		0.00	0.01	0.00	0.13***	0.00	0.02	0.00	0.02*	0.01	-0.02	0.02*	0.00	0.00	0.00
STOCKRET$_{[-10;-3]}$	0.03**	0.09***	0.02**		0.06***	0.01	0.03**	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	-0.01	-0.01	-0.01
RP_OPI	0.12***	0.02**	0.02*	0.09***		0.09***	-0.03***	-0.31***	-0.03**	-0.24***	0.02	0.00	0.06***	-0.07***	0.24***	0.20***	-0.05***
LEV	0.01	0.00	0.00	0.02**	0.06***		-0.11***	-0.25***	0.16***	-0.18***	-0.03**	0.05***	0.11***	-0.12***	0.32***	0.34***	-0.02*
ROA	-0.03**	0.29***	0.14***	0.02	0.00	-0.14***		0.38***	0.41***	0.21***	0.04***	-0.02	-0.43***	0.09***	-0.32***	-0.26***	-0.14***
SIZE	-0.19***	0.11***	0.00	-0.02	-0.23***	-0.25***	0.36***		0.29***	0.52***	-0.15***	0.00	-0.34***	0.24***	-0.78***	-0.67***	-0.04***
MB	-0.08***	0.01	0.01	0.01	0.01	0.22***	0.10***	0.09***		0.14***	0.06***	0.01	-0.14***	-0.02**	-0.12***	-0.08***	-0.18***
ANL	-0.17***	0.06***	0.00	0.01	-0.20***	-0.13***	0.17***	0.44***	0.04***		0.13***	0.01	-0.15***	0.09***	-0.35***	-0.27***	0.12***
INST	0.01	0.07***	0.01	0.01	-0.06***	-0.05***	0.08***	0.00	-0.02	0.45***		0.05***	-0.05***	0.01	0.20***	0.16***	0.07***
Q4	-0.03**	-0.03***	0.01	-0.01	-0.02	0.05***	-0.03**	0.01	0.00	0.01	0.03**		-0.04***	0.01	-0.02	-0.02	-0.01
LOSS	0.05***	-0.14***	-0.01	0.02	0.03***	0.13***	-0.39***	-0.35***	0.01	-0.16***	-0.09***	-0.04***		-0.12***	0.32***	0.28***	0.03***
HORIZON	0.02	0.01	0.02*	-0.02*	-0.05***	-0.16***	0.07***	0.16***	-0.07***	0.08***	0.05***	0.01	-0.11***		-0.18***	-0.20***	0.07***
RATING	0.07***	-0.06***	-0.01	0.00	0.16***	0.28***	-0.30***	-0.71***	0.05***	-0.26***	0.03***	-0.01	0.31***	-0.11***		0.86***	0.09***
SPEC	0.06***	-0.06***	-0.01	0.00	0.15***	0.35***	-0.24***	-0.64***	0.01	-0.22***	0.04***	-0.02	0.28***	-0.16***	0.78***		0.13***
SUBORD	0.04***	-0.01	0.00	-0.01	-0.07***	-0.01	-0.07***	-0.03**	-0.10***	0.11***	0.08***	-0.01	0.03***	0.13***	0.09***	0.13***	

The sample consists of 7,356 firm-quarter observations (1,037 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. See Appendix A for variable definition. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. In Panels B and C, figures above/below diagonal represent Spearman/Pearson correlation coefficients, and ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively.

TABLE 4
Twitter Opinion, Bond Returns and Changes in CDS Spreads around Earnings Announcements

$$BONDRET_{[-2;+2]} \text{ or } \Delta CDSSPREAD_{[-2;+2]} = \alpha + \beta_1{*}OPI_{[-10;-3]} + \beta_2{*}FE + \beta_3{*}STOCKRET_{[-2;+2]}$$
$$+ \beta_4{*}STOCKRET_{[-10;-3]} + \beta_5{*}RP\_OPI_{[-10;-3]} + \beta_6{*}LEV + \beta_7{*}ROA + \beta_8{*}SIZE$$
$$+ \beta_9{*}MB + \beta_{10}{*}ANL + \beta_{11}{*}INST + \beta_{12}{*}Q4 + \beta_{13}{*}LOSS + \beta_{14}{*}HORIZON$$
$$+ \beta_{15}{*}RATING + \beta_{16}{*}SPEC + \beta_{17}{*}SUBORD + \Sigma\delta_j{*}IND_j + \Sigma\delta_f{*}CALQTR_f + \varepsilon_{[-2;+2]}$$

Panel A: Entire Sample

Variable	$BONDRET_{[-2;+2]}$			$\Delta CDSSPREAD_{[-2;+2]}$		
	All	$FE < 0$	$FE \geq 0$	All	$FE < 0$	$FE \geq 0$
	I	II	III	IV	V	VI
OPI	**0.053*** **	**0.140*** **	**0.015**	**-0.438*** **	**-0.816*** **	**-0.224* **
	(3.18)	***(3.55)***	***(0.76)***	***(-3.68)***	***(-2.72)***	***(-1.71)***
FE	0.047	0.003	0.126**	-0.425**	-0.029	-0.799**
	(1.64)	*(0.15)*	*(2.10)*	*(-2.52)*	*(-0.18)*	*(-2.24)*
$STOCKRET_{[-2;-+2]}$	0.067***	0.074***	0.060***	-0.254***	-0.296***	-0.198***
	(13.52)	*(9.80)*	*(10.48)*	*(-8.82)*	*(-5.75)*	*(-6.07)*
$STOCKRET_{[-10;-3]}$	0.015***	0.006	0.018***	-0.086***	-0.135**	-0.049
	(3.15)	*(0.68)*	*(3.33)*	*(-2.59)*	*(-2.35)*	*(-1.24)*
RP_OPI	-0.111	0.004	-0.123	-1.301*	0.230	-1.891**
	(-0.97)	*(0.02)*	*(-1.03)*	*(-1.82)*	*(0.16)*	*(-2.31)*
LEV	-0.418***	-0.392*	-0.388**	-1.134	1.134	-1.366
	(-2.87)	*(-1.65)*	*(-2.20)*	*(-1.05)*	*(0.57)*	*(-1.01)*
ROA	-1.658	-4.849**	-0.324	5.134	-8.063	18.567
	(-1.24)	*(-2.28)*	*(-0.18)*	*(0.44)*	*(-0.37)*	*(1.44)*
SIZE	-0.045*	-0.001	-0.039	-0.239	-0.528	-0.064
	(-1.72)	*(-0.03)*	*(-1.33)*	*(-1.07)*	*(-1.15)*	*(-0.26)*
MB	0.002	-0.002	0.003	-0.052	-0.036	-0.068
	(0.31)	*(-0.18)*	*(0.49)*	*(-1.38)*	*(-0.42)*	*(-1.51)*
ANL	0.047	0.023	0.098*	0.346	0.448	-0.004
	(0.92)	*(0.21)*	*(1.70)*	*(0.94)*	*(0.65)*	*(-0.01)*
INST	-0.150	-0.419**	0.064	-0.374	-3.710	0.736
	(-1.34)	*(-2.08)*	*(0.48)*	*(-0.29)*	*(-1.54)*	*(0.66)*
Q4	0.018	0.187	-0.012	0.276	-0.741	0.625
	(0.28)	*(1.24)*	*(-0.17)*	*(0.68)*	*(-0.85)*	*(1.23)*
LOSS	0.111*	0.080	0.084	-0.882*	-0.260	-0.704
	(1.68)	*(0.73)*	*(1.02)*	*(-1.82)*	*(-0.27)*	*(-1.26)*
HORIZON	0.001	0.001	0.001	0.001	-0.001	0.001
	(0.79)	*(0.45)*	*(0.70)*	*(0.05)*	*(-1.32)*	*(1.06)*
RATING	0.002	-0.034**	0.019	-0.013	0.085	-0.072
	(0.17)	*(-2.18)*	*(1.54)*	*(-0.17)*	*(0.49)*	*(-0.83)*
SPEC	-0.153*	-0.074	-0.169*	0.699	-0.886	1.326**
	(-1.94)	*(-0.51)*	*(-1.88)*	*(1.31)*	*(-0.88)*	*(2.16)*
SUBORD	0.143**	0.164	0.108	-0.936**	-1.083	-1.064**
	(2.05)	*(1.24)*	*(1.29)*	*(-2.29)*	*(-1.08)*	*(-2.28)*
N	6,862	2,008	4,854	3,500	907	2,593
Adj. R^2 (%)	11.35	17.16	10.14	9.09	18.19	7.83

TABLE 4 (cont'd)

Panel B: Sample Partitioned by Proportion of Bond/Credit Risk-Related Tweets (%BOND)

Variable	*BONDRET*$_{[-2;+2]}$			*ΔCDSSPREAD*$_{[-2;+2]}$		
	High %BOND	*Low % BOND*	*Diff*	*High %BOND*	*Low % BOND*	*Diff*
	I	II		III	IV	
OPI	**0.100*****	**-0.003**	**0.103*****	**-0.745*****	**-0.164**	**-0.581****
	(4.30)	***(-0.12)***	***(2.85)***	***(-4.75)***	***(-0.87)***	***(-2.37)***
N	3,434	3,428		1,781	1,719	
Adj. R^2 (%)	14.35	10.88		12.20	11.13	

Panel C: Sample Partitioned by Bond Risk (Speculative-Grade vs. Investment-Grade)

Variable	*BONDRET*$_{[-2;+2]}$			*ΔCDSSPREAD*$_{[-2;+2]}$		
	Speculative	*Investment*	*Diff*	*Speculative*	*Investment*	*Diff*
	I	II		III	IV	
OPI	**0.070****	**0.048*****	**0.022**	**-0.659****	**-0.386*****	**-0.273**
	(1.97)	***(3.23)***	***(0.58)***	***(-2.02)***	***(-2.89)***	***(-0.77)***
N	2,926	3,936		749	2,751	
Adj. R^2 (%)	16.16	6.48		20.21	8.39	

Panel D: Sample Partitioned by Information Uncertainty

Variable	*BONDRET*$_{[-2;+2]}$			*ΔCDSSPREAD*$_{[-2;+2]}$		
	High Uncertainty	*Low Uncertainty*	*Diff*	*High Uncertainty*	*Low Uncertainty*	*Diff*
	I	II		III	IV	
OPI	**0.091*****	**0.022**	**0.069***	**-0.314**	**-0.592*****	**0.278**
	(2.86)	***(1.24)***	***(1.90)***	***(-1.30)***	***(-4.47)***	***(1.01)***
N	3,369	3,456		1,269	2,228	
Adj. R^2 (%)	14.82	7.45		12.82	9.21	

This table presents the regression results using standard errors clustered by firm. The sample consists of 7,356 firm-quarter observations (1,037 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. Industry and calendar quarter fixed effects are included in all panels but not reported for brevity as well as control variables in Panels B, C, and D. Panel A presents the regression results for the entire sample. Models II and V (Models III and VI) present results for the bad (good) earnings news subsample, which consists of 2,021 (4,946) firm-quarter observations, covering 696 (906) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and $FE < 0$ ($FE \geq 0$). Panel B presents the regression results for high and low *%BOND* subsamples. High (low) *%BOND* subsample consists of firm-quarter observations where the percentage of tweets with bond and/or credit risk-related words and phrases is above (below) the sample median. Panel C presents the regression results for speculative-grade and investment-grade subsamples. The speculative-grade (investment-grade) subsample consists of 3,151 (4,096) firm-quarter observations, covering 570 (531) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and traded bonds with weighted average S&P ratings below BBB- (at or above BBB-). Panel D presents the regression results for high information uncertainty and low information uncertainty subsamples. The high (low) information uncertainty subsample consists of 3,658 (3,653) firm-quarter observations, covering 678 (580) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and observations above (below) sample median stock return volatility for each calendar quarter, measured as the standard deviation of daily stock returns over the calendar year prior to the quarterly earnings announcement date. *t*-statistics are in parentheses below coefficient estimates. For the variables of interest, coefficient estimates and *t*-statistics are bolded. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 5
Twitter Opinion and Future Changes in Bond Yield Spreads

$$\Delta YIELD_{[q\text{-}1;q+k]} = \alpha + \beta_1{*}OPI_{[-10;-3]} + \beta_2{*}FE + \beta_3{*}STOCKRET_{[-2;+2]} + \beta_4{*}STOCKRET_{[-10;-3]} + \beta_5{*}RP\_OPI_{[-10;-3]} + \beta_6{*}LEV + \beta_7{*}ROA + \beta_8{*}SIZE + \beta_9{*}MB + \beta_{10}{*}HORIZON + \beta_{11}{*}RATING + \beta_{12}{*}SPEC + \beta_{13}{*}SUBORD + \Sigma\delta_j{*}IND_j + \Sigma\delta_f{*}CALQTR_f + \varepsilon_{[q\text{-}1;q+k]}$$

Panel A: Entire Sample

Variable	*ΔYIELD* [*q*-1;*q*+1] I	*ΔYIELD* [*q*-1;*q*+3] II
OPI	**-0.166*****	**-0.269*****
	(-3.29)	***(-3.58)***
FE	-0.211***	-0.022
	(-2.60)	*(-0.22)*
$STOCKRET_{[-2;-+2]}$	-0.005	0.004
	(-0.52)	*(0.33)*
$STOCKRET_{[-10;-3]}$	0.017	-0.027*
	(1.40)	*(-1.70)*
RP_OPI	0.241	0.194
	(1.04)	*(0.60)*
LEV	-1.159***	-1.553**
	(-2.70)	*(-2.33)*
ROA	5.892	9.436*
	(1.28)	*(1.88)*
SIZE	0.270***	0.434***
	(3.51)	*(3.50)*
MB	0.035	0.081*
	(1.62)	*(1.64)*
HORIZON	0.001	0.001
	(0.04)	*(0.29)*
RATING	0.173***	0.314***
	(3.89)	*(4.20)*
SPEC	-0.351	-0.547
	(-1.44)	*(-1.33)*
SUBORD	0.031	-0.137
	(0.17)	*(-0.53)*
N	5,402	5,228
Adj. R^2 (%)	4.15	7.31

TABLE 5 (cont'd)

Panel B: Sample Partitioned by Proportion of Bond/Credit Risk-Related Tweets (%BOND)

Variable	$\Delta YIELD_{[q-1;q+1]}$		
	High %BOND	*Low % BOND*	*Diff*
	I	II	
OPI	**-0.210*****	**-0.120**	**-0.090**
	(-3.27)	***(-1.40)***	***(-0.84)***
N	2,742	2,660	
Adj. R^2 (%)	5.97	5.18	

Panel C: Sample Partitioned by Bond Risk (Speculative-Grade vs. Investment-Grade)

Variable	$\Delta YIELD_{[q-1;q+1]}$		
	Speculative	*Investment*	*Diff*
	I	II	
OPI	**-0.362*****	**-0.127*****	**-0.235***
	(-2.73)	***(-3.98)***	***(-1.72)***
N	1,954	3,448	
Adj. R^2 (%)	8.86	4.95	

Panel D: Sample Partitioned by Information Uncertainty

Variable	$\Delta YIELD_{[q-1;q+1]}$		
	High Uncertainty	*Low Uncertainty*	*Diff*
	I	II	
OPI	**-0.380*****	**-0.061**	**-0.319*****
	(-4.20)	***(-0.86)***	***(-2.77)***
N	2,483	2,891	
Adj. R^2 (%)	5.00	9.32	

This table presents the regression results using standard errors clustered by firm. The sample consists of 7,356 firm-quarter observations (1,037 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. Industry and calendar quarter fixed effects are included in all panels but not reported for brevity as well as control variables in Panels B, C, and D. Panel A presents the regression results for the entire sample. Panel B presents the regression results for high and low *%BOND* subsamples. High (low) *%BOND* subsample consists of firm-quarter observations where the percentage of tweets with bond and/or credit risk-related words and phrases is above (below) the sample median. Panel C presents the regression results for speculative-grade and investment-grade subsamples. The speculative-grade (investment-grade) subsample consists of 3,151 (4,096) firm-quarter observations, covering 570 (531) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and traded bonds with weighted average S&P ratings below BBB- (at or above BBB-). Panel D presents the regression results for high information uncertainty and low information uncertainty subsamples. The high (low) information uncertainty subsample consists of 3,658 (3,653) firm-quarter observations, covering 678 (580) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and observations above (below) sample median stock return volatility for each calendar quarter, measured as the standard deviation of daily stock returns over the calendar year prior to the quarterly earnings announcement date. *t*-statistics are in parentheses below coefficient estimates. For the variables of interest, coefficient estimates and *t*-statistics are bolded. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 6
Twitter Opinion and Future Changes in Credit Ratings

$$\log\left(\frac{\Pr(\Delta RATING_{[-2;+t]} = -1, 1)}{\Pr(\Delta RATING_{[-2;+t]} = 0)}\right) = \alpha + \beta_1 * OPI_{[-10;-3]} + \beta_2 * FE + \beta_3 * STOCKRET_{[-2;+2]} + \beta_4 * STOCKRET_{[-10;-3]}$$
$$+ \beta_5 * RP\_OPI_{[-10;-3]} + \beta_6 * LEV + \beta_7 * ROA + \beta_8 * SIZE + \beta_9 * MB + \beta_{10} * HORIZON$$
$$+ \beta_{11} * RATING + \beta_{12} * SPEC + \beta_{13} * SUBORD + \Sigma\delta_j * IND_j + \Sigma\delta_f * CALQTR_f + \varepsilon_{[-2;+t]}$$

Variable	[-2;+65]		[-2;+190]	
	DOWN GRADE	*UP GRADE*	*DOWN GRADE*	*UP GRADE*
	I	II	III	IV
OPI	**-0.250*****	**-0.066**	**-0.259*****	**0.013**
	(-3.97)	***(-1.00)***	***(-4.69)***	***(0.24)***
FE	-0.133***	0.035	-0.140***	0.100**
	(-2.93)	*(0.63)*	*(-3.34)*	*(2.47)*
$STOCKRET_{[-2;-+2]}$	-0.026***	0.005	-0.021***	0.011**
	(-2.82)	*(0.60)*	*(-3.10)*	*(2.03)*
$STOCKRET_{[-10;-3]}$	-0.007	-0.001	-0.012	-0.001
	(-0.61)	*(-0.10)*	*(-1.43)*	*(-0.14)*
RP_OPI	-1.060***	-0.028	-0.522**	-0.098
	(-3.26)	*(-0.07)*	*(-1.96)*	*(-0.36)*
LEV	1.494***	-0.061	1.996***	-0.170
	(3.23)	*(-0.13)*	*(4.15)*	*(-0.43)*
ROA	-13.214***	11.864**	-14.136***	8.772***
	(-4.48)	*(2.36)*	*(-4.81)*	*(2.75)*
SIZE	-0.515***	0.026	-0.563***	-0.015
	(-6.51)	*(0.39)*	*(-7.05)*	*(-0.23)*
MB	-0.058	0.020	-0.018	0.016
	(-1.58)	*(1.12)*	*(-0.75)*	*(1.09)*
HORIZON	-0.001*	-0.001*	-0.001***	-0.001***
	(-1.89)	*(-1.94)*	*(-2.51)*	*(-2.84)*
RATING	-0.282***	-0.029	-0.342***	-0.044**
	(-8.68)	*(-1.37)*	*(-10.29)*	*(-2.21)*
SPEC	0.966***	1.489***	1.190***	1.369***
	(3.35)	*(6.18)*	*(4.36)*	*(6.46)*
SUBORD	0.485***	0.071	0.541***	0.192
	(2.60)	*(0.37)*	*(2.95)*	*(1.10)*
N	6,862		6,862	
N *DOWNGRADE*=1	321		699	
N *UPGRADE*=1	274		707	
Pseudo R^2 (%)	12.59		13.02	

TABLE 6 (cont'd)

Panel B: Sample Partitioned by Proportion of Bond/Credit Risk-Related Tweets (%BOND)

Variable	*DOWNGRADE*$_{[-2;+65]}$			*UPGRADE*$_{[-2;+65]}$		
	High %BOND	*Low %BOND*	*Diff*	*High %BOND*	*Low %BOND*	*Diff*
	I	II		III	IV	
OPI	**-0.278*****	**-0.199****	**-0.078**	**-0.052**	**-0.040**	**-0.013**
	(-3.32)	***(-2.07)***	***(-0.61)***	***(-0.56)***	***(-0.41)***	***(-0.09)***
N	3,434	3,428		3,434	3,428	
N *DOWNGRADE=1*	170	151		170	151	
N *UPGRADE*=1	138	136		138	136	
Pseudo R^2 (%)	15.56	15.20		15.56	15.20	

Panel C: Sample Partitioned by Bond Risk (Speculative-Grade vs. Investment-Grade)

Variable	*DOWNGRADE*$_{[-2;+65]}$			*UPGRADE*$_{[-2;+65]}$		
	Speculative	*Investment*	*Diff*	*Speculative*	*Investment*	*Diff*
	I	II		III	IV	
OPI	**-0.356*****	**-0.107**	**-0.249***	**-0.007**	**-0.112**	**0.105**
	(-3.77)	***(-1.20)***	***(-1.92)***	***(-0.08)***	***(-1.03)***	***(0.74)***
N	2,926	3,936		2,926	3,936	
N *DOWNGRADE*=1	156	165		156	165	
N *UPGRADE*=1	181	93		181	93	
Pseudo R^2 (%)	14.09	17.52		14.09	17.52	

Panel D: Sample Partitioned by Information Uncertainty

Variable	*DOWNGRADE*$_{[-2;+65]}$			*UPGRADE*$_{[-2;+65]}$		
	High Uncertainty	*Low Uncertainty*	*Diff*	*High Uncertainty*	*Low Uncertainty*	*Diff*
	I	II		III	IV	
OPI	**-0.247*****	**-0.187****	**-0.059**	**-0.003**	**-0.104**	**0.101**
	(-3.06)	***(-2.03)***	***(-0.48)***	***(-0.03)***	***(-1.02)***	***(0.74)***
N	3,369	3,456		3,369	3,456	
N *DOWNGRADE*=1	226	94		226	94	
N *UPGRADE*=1	166	102		166	102	
Pseudo R^2 (%)	17.66	9.70		10.69	10.18	

This table presents the multinomial logit regression results using standard errors clustered by firm. The sample consists of 7,356 firm-quarter observations (1,037 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. Industry and calendar quarter fixed effects are included in all panels but not reported for brevity as well as control variables in Panels B, C, and D. Panel A presents the regression results for the entire sample. Panel B presents the regression results for high and low *%BOND* subsamples. High (low) *%BOND* subsample consists of firm-quarter observations where the percentage of tweets with bond and/or credit risk-related words and phrases is above (below) the sample median. Panel C presents the regression results for speculative-grade and investment-grade subsamples. The speculative-grade (investment-grade) subsample consists of 3,151 (4,096) firm-quarter observations, covering 570 (531) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and traded bonds with weighted average S&P ratings below BBB- (at or above BBB-). Panel D presents the separate logit regression results for high information uncertainty and low information uncertainty subsamples. The high (low) information uncertainty subsample consists of 3,658 (3,653) firm-quarter observations, covering 678 (580) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and observations above (below) sample median stock return volatility for each calendar quarter, measured as the standard deviation of daily stock returns over the calendar year prior to the quarterly earnings announcement date. *z*-statistics (and *t*-statistics for Panels B, C, and D) are in parentheses below coefficient estimates. For the variables of interest, coefficient estimates, *z*-statistics, and *t*-statistics are bolded. ***, **, * represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 7
Twitter Opinion and Future Changes in Implied Default Probability

$$\Delta PROB_{[q-1;q+k]} = \alpha + \beta_1 * OPI_{[-10;-3]} + \beta_2 * FE + \beta_3 * STOCKRET_{[-2;+2]} + \beta_4 * STOCKRET_{[-10;-3]} + \beta_5 * RP\_OPI_{[-10;-3]} + \beta_6 * LEV + \beta_7 * ROA + \beta_8 * SIZE + \beta_9 * MB + \beta_{10} * HORIZON + \beta_{11} * RATING + \beta_{12} * SPEC + \beta_{13} * SUBORD + \Sigma\delta_j * IND_j + \Sigma\delta_f * CALQTR_f + \varepsilon_{[q-1;q+k]}$$

Panel A: Entire Sample

Variable	*ΔZ-PROB*		*ΔO-PROB*		*ΔBSM-PROB*	
	[*q*-1;*q*+1]	[*q*-1;*q*+3]	[*q*-1;*q*+1]	[*q*-1;*q*+3]	[*q*-1;*q*+1]	[*q*-1;*q*+3]
	I	II	III	IV	V	VI
OPI	**-0.544*****	**-0.943*****	**-0.173*****	**-0.294*****	**-1.982*****	**-2.811*****
	(-6.28)	***(-8.28)***	***(-2.84)***	***(-4.55)***	***(-10.78)***	***(-10.65)***
FE	-0.417***	-0.249	-0.149	-0.044	-1.443***	-0.410
	(-2.89)	*(-1.60)*	*(-0.99)*	*(-0.29)*	*(-3.85)*	*(-0.82)*
$STOCKRET_{[-2;-+2]}$	-0.102***	-0.105***	-0.041***	-0.034**	-0.137***	-0.160***
	(-5.66)	*(-5.39)*	*(-3.07)*	*(-2.55)*	*(-3.48)*	*(-3.32)*
$STOCKRET_{[-10;-3]}$	-0.055**	-0.069**	0.009	-0.019	-0.071	-0.118**
	(-2.24)	*(-2.57)*	*(0.47)*	*(-0.98)*	*(-1.50)*	*(-1.97)*
RP_OPI	-0.397	0.713	-0.150	0.062	0.696	4.785***
	(-0.66)	*(1.03)*	*(-0.36)*	*(0.14)*	*(0.74)*	*(3.62)*
LEV	-1.947***	-3.109***	-0.946	-0.552	-4.499***	-8.042***
	(-2.58)	*(-3.04)*	*(-1.24)*	*(-0.81)*	*(-2.97)*	*(-3.60)*
ROA	-26.972***	-4.646	-5.896	2.047	25.240*	66.047***
	(-3.01)	*(-0.36)*	*(-0.96)*	*(0.35)*	*(1.83)*	*(3.30)*
SIZE	0.111	-0.009	0.029	0.081	0.294	1.378***
	(1.07)	*(-0.06)*	*(0.30)*	*(0.91)*	*(1.44)*	*(4.59)*
MB	-0.055	-0.016	-0.085**	-0.102***	-0.003	0.149
	(-1.34)	*(-0.33)*	*(-2.19)*	*(-2.87)*	*(-0.04)*	*(1.48)*
HORIZON	-0.001	-0.001	-0.001	-0.001**	0.001	0.001
	(-0.11)	*(-0.10)*	*(-0.66)*	*(-2.20)*	*(0.68)*	*(0.60)*
RATING	0.046	0.084	0.014	0.044	0.091	0.373***
	(1.12)	*(1.30)*	*(0.50)*	*(1.62)*	*(1.28)*	*(3.52)*
SPEC	0.110	0.212	0.130	0.009	-0.624	-0.061
	(0.35)	*(0.48)*	*(0.72)*	*(0.05)*	*(-1.04)*	*(-0.06)*
SUBORD	-0.227	-0.243	-0.083	-0.189	-1.222**	-1.813*
	(-0.74)	*(-0.52)*	*(-0.40)*	*(-0.72)*	*(-2.15)*	*(-1.86)*
N	6,227	6,107	5,368	5,276	6,755	6,749
Adj. R^2 (%)	5.97	6.73	3.15	2.71	7.41	8.78

TABLE 7 (cont'd)

Panel B: Sample Partitioned by Proportion of Bond/Credit Risk-Related Tweets (%BOND)

Variable	Δ*Z-PROB*$_{[q\text{-}1;q+1]}$			Δ*O-PROB*$_{[q\text{-}1;q+1]}$			Δ*BSM-PROB*$_{[q\text{-}1;q+1]}$		
	High %BOND	*Low %BOND*	*Diff*	*High %BOND*	*Low %BOND*	*Diff*	*High %BOND*	*Low %BOND*	*Diff*
	I	II		III	IV		V	VI	
OPI	**-0.478*****	**-0.647*****	**0.169**	**-0.176****	**-0.173****	**-0.004**	**-2.051*****	**-1.901*****	**-0.150**
	(-4.17)	***(-4.94)***	***(0.97)***	***(-1.98)***	***(-1.99)***	***(-0.03)***	***(-7.67)***	***(-7.75)***	***(-0.41)***
N	3,068	3,159		2,585	2,783		3,379	3,376	
Adj. R^2 (%)	6.69	7.44		4.32	4.71		8.43	8.57	

Panel C: Sample Partitioned by Bond Risk (Speculative-Grade vs. Investment-Grade)

Variable	Δ*Z-PROB*$_{[q\text{-}1;q+1]}$			Δ*O-PROB*$_{[q\text{-}1;q+1]}$			Δ*BSM-PROB*$_{[q\text{-}1;q+1]}$		
	Spec.	*Inv.*	*Diff*	*Spec.*	*Inv.*	*Diff*	*Spec.*	*Inv.*	*Diff*
	I	II		III	IV		V	VI	
OPI	**-0.750*****	**-0.368*****	**-0.382***	**-0.422****	**-0.041****	**-0.382****	**-3.372*****	**-1.153*****	**-2.218*****
	(-3.89)	***(-5.61)***	***(-1.87)***	***(-2.37)***	***(-2.31)***	***(-2.13)***	***(-8.44)***	***(-7.68)***	***(-5.20)***
N	2,745	3,482		2,516	2,852		2,852	3,903	
Adj. R^2 (%)	7.96	5.55		4.95	5.12		9.55	8.59	

Panel D: Sample Partitioned by Information Uncertainty

Variable	Δ*Z-PROB*$_{[q\text{-}1;q+1]}$			Δ*O-PROB*$_{[q\text{-}1;q+1]}$			Δ*BSM-PROB*$_{[q\text{-}1;q+1]}$		
	High Uncert.	*Low Uncert.*	*Diff*	*High Uncert.*	*Low Uncert.*	*Diff*	*High Uncert.*	*Low Uncert.*	*Diff*
	I	II		III	IV		V	VI	
OPI	**-0.942*****	**-0.215*****	**-0.726*****	**-0.493*****	**-0.021**	**-0.472*****	**-3.817*****	**-0.356*****	**-3.461*****
	(-5.04)	***(-3.60)***	***(-3.70)***	***(-2.93)***	***(-1.29)***	***(-2.80)***	***(-10.83)***	***(-5.24)***	***(-9.64)***
N	2,981	3,217		2,494	2,841		3,311	3,428	
Adj. R^2 (%)	7.86	6.07		5.08	4.93		10.31	6.46	

This table presents the regression results using standard errors clustered by firm. Changes in implied default probability (in %) are estimated based on changes in Z-Score (*Z-PROB*), O-Score (*O-PROB*), and the Black-Scholes-Merton model (*BSM-PROB*) between quarter q-1 and either quarter q+1 or quarter q+3, where quarter q is the quarter during which *OPI* is measured. The sample consists of 7,356 firm-quarter observations (1,037 distinct firms), with quarterly earnings announcement dates between January 1, 2009 and December 31, 2012. Industry and calendar quarter fixed effects are included in all panels but not reported for brevity as well as control variables in Panels B, C, and D. Panel A presents the regressions for the entire sample. Panel B of this table presents the regression results for high and low *%BOND* subsamples. High (low) *%BOND* subsample consists of firm-quarter observations where the percentage of tweets with bond and/or credit risk-related words and phrases is above (below) the sample median. Panel C presents the regression results for speculative-grade and investment-grade subsamples. The speculative-grade (investment-grade) subsample consists of 3,151 (4,096) firm-quarter observations, covering 570 (531) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and traded bonds with weighted average S&P ratings below BBB- (at or above BBB-). Panel D presents the regression results for high information uncertainty and low information uncertainty subsamples. The high (low) information uncertainty subsample consists of 3,658 (3,653) firm-quarter observations, covering 678 (580) distinct firms, with earnings announcement dates between January 1, 2009 and December 31, 2012, and observations above (below) sample median stock return volatility for each calendar quarter, measured as the standard deviation of daily stock returns over the calendar year prior to the quarterly earnings announcement date. t-statistics are in parentheses below coefficient estimates. For the variables of interest, coefficient estimates and t-statistics are bolded. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.