The Relevance of Credit Ratings in Transparent Bond Markets*

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Abstract

This paper examines how public dissemination (or disclosure) of corporate bond transactions via the TRACE system affects the information content and relevance of credit ratings. We find that dissemination reduces the average short-term stock price impact of rating downgrades from 3.7% to 0.9%, suggesting that the transparency of market prices reduces information gaps and hence reliance on intermediaries. The impact of dissemination is smaller where the issuer is a CDS reference entity or has outstanding bonds traded on an exchange or where stock analysts issue more reliable earnings forecasts. We also find evidence that rating agencies provide more timely and accurate ratings after dissemination. Finally, we document that dissemination enhances the ability of credit spreads to predict future defaults and increases the flow of information from the bond market to the equity market before important credit events, consistent with more efficient information aggregation and transmission in transparent markets.

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Credit rating agencies are financial intermediaries that provide standardized opinions on the creditworthiness of debt issuers or specific debt obligations. They add value either by reducing investors' information processing costs or by transmitting material non-public information. When transaction prices are readily available to investors, credit markets perform a similar informational role. In particular, when transparent, credit markets aggregate default-relevant public and private information via the trading process and transmit this information to investors through the level of or changes in bond prices.[1]

This paper examines how the introduction of post-trade transparency in corporate bonds affects the relevance and information content of credit ratings. To identify the causal impact of trade transparency, we use a recent regulation in the U.S. that mandates real-time public dissemination of information on all over-the-counter (OTC) transactions in corporate debt securities (including the price, yield, and volume of trades) via the Trade Reporting and Compliance Engine (TRACE).[2] Before the introduction of TRACE in July 2002, the corporate bond market was one of the least transparent securities markets in the U.S.: Neither dealer quotations nor completed transactions were reported broadly or continuously, resulting in substantial price uncertainty. Past studies document a significant decline in bond price dispersion after the introduction of TRACE dissemination, suggesting that once prices of recent transactions become common knowledge investors better assess the fairness of prices offered to them.[3]

The introduction of TRACE provides an ideal quasi-experiment to estimate the effect of transparency on the information content of credit ratings. The most useful feature of this experiment from an identification standpoint is that dissemination was implemented in multiple phases between July 2002 and February 2005. In consequence, cross-sectional and time-series variations in dissemination permit the use of firm and time fixed effects in our regression

[1]See Bond, Edmans, and Goldstein (2012) for an excellent review of both theoretical and empirical research that examine the informational role of market prices.

[2]Initially, investors were able to access TRACE data free of charge through websites such as the National Association of Securities Dealers' (NASD's) nasdbondinfo.com or the Bond Markets Association's investinginbonds.com. Additionally, the data could be accessed through market data vendors such as Bloomberg and Reuters (Vames, 2003). As of this writing, TRACE data is publicly available through http://finra-markets.morningstar.com/BondCenter/Default.jsp.

[3]See, for example, Bessembinder, Maxwell, and Venkataraman (2006), Bessembinder and Maxwell (2008), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), Asquith, Covert, and Pathak (2013), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2016).

models to reduce concerns about omitted variables bias. For example, we estimate models with firm fixed effects to control for time-invariant differences in rating informativeness due to unexplained factors that differ across firms. We also add time fixed effects to control for time-series changes in credit markets or investor confidence in rating agencies. Moreover, we include phase dummies to address a possible concern that dissemination decisions were in part based on expected changes in rating informativeness. As discussed later, the selection of bonds for each dissemination phase was primarily based on two observable bond characteristics: rating and original issue size. Conditional on other controls, the phase dummies are weakly correlated with our main measure of rating informativeness, mitigating potential endogeneity concerns.

Another important advantage of the TRACE experiment is that we have access to prices and yields of both disseminated and non-disseminated historical bond transactions through the Enhanced TRACE database. Using those transactions and difference-in-differences regressions, we estimate the causal effect of dissemination on (i) the sensitivity of credit ratings to credit spreads, and (ii) the ability of credit spreads to aggregate information about credit risk.

We begin our empirical analysis by examining the effect of dissemination on the informational value of credit ratings. Past studies generally measure the value of ratings using the short-term stock or bond price reaction to announcements of rating revisions.[4] The prevailing evidence is that rating downgrades (but not rating upgrades) convey valuable information to market participants, in the sense that, on average, they significantly move stock and bond prices.[5] Thus, we estimate the effect of dissemination on rating informativeness by comparing the average short-term (i.e., three-day) impact of rating downgrades on security prices before and after dissemination.[6] Our sample consists of 1,803 bond rating downgrades by the Big Three rating agencies (Standard & Poor's (S&P), Moody's, and Fitch). Our sample period is between July 1, 2001 (one year before the introduction of TRACE) and February 7,

[4]See, e.g., Weinstein (1977), Holthausen and Leftwich (1986), Ederington, Yawitz, and Roberts (1987), Hand, Holthausen, and Leftwich (1992), Goh and Ederington (1993), Hite and Warga (1997), Dichev and Piotroski (2001), Jorion, Liu, and Shi (2005), and Chava, Ganduri, and Ornthanalai (2016).

[5]The lack of a significant market reaction to upgrades is consistent with the view in Ederington et al. (1987) that rating agencies expend more resources to detect deteriorations in credit quality than improvements.

[6]Consistent with past studies, we find no significant price effect of rating upgrades, either before or after dissemination; as such, in this paper, we focus on rating downgrades.

2006 (one year after the full implementation of TRACE dissemination). Our sample of rating downgrades come from Mergent's Fixed Income Securities Database (FISD).

In the time-series, we find that quarterly average of abnormal stock returns associated with rating downgrades are negative and exhibit a downward trend (becoming bigger in absolute value) in the year before the introduction of TRACE. However, they exhibit an upward trend from the introduction of TRACE until the end of our sample period—they converge to zero as the fraction of disseminated bond transactions converges to one—which indicates that dissemination reduces the incremental informativeness of rating downgrades. In the cross-section, we find that the average abnormal stock return associated with rating downgrades is -3.7% for issuers with non-disseminated bonds and -0.9% for those with disseminated bonds. The difference (2.8%) is economically large and statistically significant at the 1% level.

We estimate the causal effect of dissemination in a regression framework where we control for (i) the dissemination phase of the issuer's bonds, (ii) factors that have been shown by previous research to affect the stock price impact of rating downgrades (including a CDS reference entity indicator), and (iii) firm (or industry) and year-quarter fixed effects. When we include year-quarter dummies in our regression models, we attribute all of the time-series variation in abnormal stock returns to factors other than dissemination, or in other words, conservatively estimate the overall effect of dissemination. Regression estimates of the effect of dissemination on announcement returns range between 1.6% and 3.3% and are all statistically significant at the 1% level. The results are robust to using alternative benchmark pricing models or event windows, scaling abnormal returns by residual stock volatility, focusing on downgrades during the TRACE implementation window, and excluding downgrades that coincide with major firm-specific news announcements. Interestingly, in the subsample of downgrades that do not coincide with major contemporaneous news announcements, the average stock price impact is indistinguishable from zero post-dissemination.

Goh and Ederington (1993) note that while an unanticipated downgrade is unambiguously bad news for *bondholders*, downgrades are good news for *stockholders* when they inform market participants about an unanticipated increase in the volatility of an issuer's asset values. To address a possible concern that more of the downgrades in the dissemination group could be induced by volatility news, we also examine abnormal *bond* returns around rating downgrades and find that dissemination reduces the abnormal bond price impact of rating downgrades by between 1.9% and 3.3%.

The regression results are robust to the inclusion of time dummies, mitigating the possibility that our results are driven by uncontrolled time-series changes in investor confidence in issuer-paid ratings.[7] Nonetheless, we address the issue of investor confidence by conducting a couple of tests. First, we examine rating downgrades by the *investor-paid* Egan-Jones Ratings (EJR) and find that dissemination reduces the average stock price impact of EJR's rating downgrades by between 3.0% and 4.9% (significant at the 5% level or higher). Second, for a group of issuers with no outstanding bonds, we examine the annual average stock price impact of *loan* rating downgrades by S&P and find no significant time trend during our sample period. These results reinforce the conclusion that we identify a causal effect of dissemination.

Cross-sectionally, we find that dissemination has a smaller effect on abnormal stock returns where alternative market-based indicators of credit risk are available—particularly, where the issuer is a CDS reference entity or has outstanding bonds traded on an exchange or where stock analysts issue more reliable forecasts of the issuer's future earnings. However, credit default swaps and exchange trading do not appear to be perfect substitutes for transparent bond yields.[8] We also find that the effect of dissemination is considerably smaller for investment grade bonds, where credit risk is a smaller fraction of the observed yield spreads (Huang and Huang, 2012).

We formally test the hypothesis that stock investors learn from transparent bond prices, using a daily panel of stock and bond returns and an estimation strategy first proposed by Kwan (1996). Before dissemination, we find no systematic flow of information from the bond market to the equity market. After dissemination, however, we identify a significant information flow, which dramatically increases during the month before rating downgrades. This finding is consistent with dissemination facilitating the transmission of credit risk information from the bond market to the equity market.

The evidence so far is consistent with the view that credit ratings are a substantially

[7] Marandola and Mossucca (2016) argue that corporate governance scandals in the early 2000s diminished investor confidence in credit rating agencies.

[8] Chava et al. (2016) provide evidence that credit ratings are a less relevant source of information in the presence of CDS trading. We confirm their result in our sample.

less important source of information in transparent bond markets. In the second part of the paper, we examine how dissemination affects the information content of credit ratings, using a monthly panel of issuer ratings and trade-weighted average credit spreads. We hypothesize that, after dissemination, credit ratings will become more accurate predictors of default and more sensitive to the changes in credit spreads. There are two reasons for why we would expect this to be the case. First, rating agencies might incorporate the additional information learned from transparent bond prices into their models. Second, transparent bond prices might elevate rating agencies' reputational concerns because they make it easier for investors to detect inflated issuer-paid ratings. Overall, consistent with this hypothesis, we find that issuer-paid ratings better predict default and more accurately sort firms based on their default risk after dissemination. These results also mitigate a possible concern that reductions in the short-term price impact of rating downgrades after dissemination could arise from reductions in ratings quality.

The third part of the paper examines the effect of dissemination on the production and aggregation of default-relevant information in corporate bond markets. Dissemination could reduce the informativeness of bond prices by reducing investors' incentives to acquire private information (Diamond, 1985) or leading investors to move their trades to less transparent markets (Bloomfield and O'Hara, 2000). However, dissemination could also facilitate information aggregation by allowing informed speculators to identify and correct mispricing. The question of which of these effects dominates is an empirical one. To answer it, we compare how well credit spreads predict future default before and after dissemination using difference-in-differences regressions. We find that the predictive power of credit spreads increases significantly after dissemination. This suggests that bond prices contain more default-relevant information after dissemination, which is consistent with more efficient information aggregation.

Finally, we examine whether credit spreads can serve as viable substitutes for credit ratings in predicting defaults. When we run a horse race between the two measures, the clear winner is credit spreads, with ratings having no significant incremental explanatory power. Moreover, in the post-dissemination period, models based on credit spreads correctly identify more of the defaulters than models based on credit ratings (26.9% versus 15.4%), although they also produce more false positives (0.31% versus 0.19%). Models based on both credit spreads and credit ratings do better on both fronts relative to models based on credit spreads alone, which suggests that the two measures of credit risk could serve as complements (see Chava et al. (2016) for a similar argument concerning CDS spreads and ratings).

Our paper contributes to several strands of research. First, we extend the literature on the informational role of rating agencies by presenting evidence that the primary function of credit ratings is to fill information gaps arising from the absence of readily available market prices. Second, we contribute to the literature on conflicts of interest in the rating industry by presenting evidence that transparent market prices serve as a disciplinary mechanism and enhance the quality (i.e., ex post accuracy) of agency ratings.[9] Third, we find that markets play their theoretical information aggregation and transmission roles most effectively where prices of trades are transparent.[10] Fourth, we contribute to the policy debate on the benefits and costs of mandated transaction reporting in OTC markets by presenting evidence that a previously overlooked benefit of transaction reporting is to facilitate aggregation and transmission of information, especially for high yield securities where mandated transparency rules are most hotly contested (see, e.g., Asquith et al. (2013)). Finally, our paper contributes to a growing literature examining whether market-based indicators of credit risk are viable substitutes for credit ratings.[11] We find that credit ratings are a substantially less relevant

[9] For evidence that rating agencies cater to issuers in the corporate bond market by issuing inflated ratings, see Jiang, Stanford, and Xie (2012), Cornaggia and Cornaggia (2013), Xia (2014), and Badoer, Demiroglu, and James (2017). Piccolo and Shapiro (2016) predict that informative market prices make rating inflation more transparent, and thereby increase the incentives for rating agencies to issue more accurate ratings. Gopalan, Gopalan, and Koharki (2017) document that, in India, rating agencies are more likely to cater to issuers without publicly listed stocks. Moreover, Xia (2014) shows that initiation of ratings coverage by investor-paid rating agencies has a similar disciplinary effect on the ratings of issuer-paid agencies.

[10] A large body of theoretical research predicts that financial markets aggregate diverse pieces of information held by speculative traders and transmit this information to market participants through the price mechanism (Hayek, 1945; Grossman, 1976, 1978; Grossman and Stiglitz, 1980; Hellwig, 1980; Diamond and Verrecchia, 1981; Bond and Goldstein, 2015). Consistent with these models, a number of recent empirical studies including Luo (2005), Chen, Goldstein, and Jiang (2007), Bakke and Whited (2010), Edmans, Goldstein, and Jiang (2012), Foucault and Fresard (2014), and Edmans, Jayaraman, and Schneemeier (2016) provide evidence that corporate managers learn from the private information embedded in stock prices and incorporate this information in their investment decisions. Moreover, Demiroglu, Franks, and Lewis (2016) find that the introduction of TRACE dissemination has dramatically reduced court misvaluations and inter-claimant wealth transfers in U.S. Chapter 11 bankruptcy proceedings, consistent with market prices of bonds providing information to bankruptcy participants and courts. Moreover, Chen and Lu (2016) find that transaction reporting via TRACE has significantly enhanced the informational efficiency of the corporate bond prices.

[11] See, e.g., Partnoy (1999, 2006); Flannery, Houston, and Partnoy (2010); Chava et al. (2016). A number of recent papers provide evidence that rating agencies contributed to the 2007-2008 financial crisis through their role in rating mortgage-backed securities (Benmelech and Dlugosz, 2010; Ashcraft, Goldsmith-Pinkham, and Vickery, 2010; Griffin and Tang, 2012; He, Qian, and Strahan, 2012, 2016). Others find that systematic errors in ratings

source of information in transparent bond markets and they are less accurate predictors of default than credit spreads. However, we also find that credit spreads more frequently produce potentially costly false positives. In our empirical analyses, we do not separate credit spreads into default and non-default components. Neither do we estimate the costs and benefits associated with greater accuracy versus false positive. Thus, more research is required to evaluate the substitutability of credit ratings and credit spreads.[12]

The rest of this paper is organized as follows. In Section 1, we provide a brief description of TRACE. Section 2 describes our data sources. Section 3 examines how dissemination affects the stock and bond price impact of rating downgrades. We examine the flow of information from the bond market to the equity market in Section 4. Section 5 examines how dissemination affects the relation between credit ratings and credit spreads and the ability of both variables to predict future default. Section 6 provides our conclusions.

1 Background on TRACE

In this section, we provide a brief overview of the microstructure of corporate bond markets and the implementation of TRACE. More detailed discussions are available in a number of sources, including Biais and Green (2007), Bessembinder and Maxwell (2008), and Asquith et al. (2013).

Corporate debt securities are generally traded in decentralized OTC markets intermediated by dealers. While there is also some trading activity in the New York Stock Exchange (NYSE), only a small fraction of bond issues are listed there and a substantial fraction of the trades for the listed securities are carried out OTC (Hite and Warga (1997), Edwards et al. (2007)).[13]

distort firm financing and investment decisions (Baghai, Servaes, and Tamayo, 2014; Harford, Martos-Vila, and Rhodes-Kropf, 2015). These distortions have led regulators and legislators to reform the rating industry and seek viable alternatives to credit ratings. For example, the Dodd-Frank Wall Street Reform and Consumer Protection Act includes provisions to eliminate regulatory reliance on ratings. Dimitrov, Palia, and Tang (2015) find that following Dodd-Frank issuer-paid rating agencies issue lower and less informative ratings. Jankowitsch, Ottonello, and Subrahmanyam (2017) find that, after the introduction of Dodd-Frank, the informativeness of rating changes improves for some but not all securities.

[12] As Chava et al. (2016) explain, market prices provide point-in-time, risk neutral assessments of credit risk, whereas ratings reflect objective, through-the-cycle assessments. As a result, the two measures may not be perfect substitutes and could be relevant for different purposes.

[13] Biais and Green (2007) provide evidence that before World War II, there was an active corporate bond market on the NYSE, but trading migrated largely to OTC markets after the mid-1940s. They attribute the migration to

Prior to the implementation of TRACE, corporate debt markets were characterized by asymmetric information (Bessembinder and Maxwell, 2008). There was limited pre-trade transparency (i.e., quotations, or prices at which dealers or other market participants are willing to trade, were not widely disseminated) or post-trade transparency (i.e., completed transactions were not systematically reported to third parties).[14] As a result, institutional investors relied mainly on telephone quotations from dealers and price estimates ("matrix prices") from data vendors such as Merrill Lynch Bond Pricing Service or Interactive Data Corporation to estimate the value of their bond holdings.[15] Individual investors had access to even less information and relied mainly on quotations from retail brokerage firms.

In 1998, the SEC called upon the NASD to take the following three steps to provide greater transparency to investors and enhance the integrity of the corporate debt markets: "(1) adopt rules requiring NASD members to report all transactions in corporate bonds to the NASD and to develop systems to receive and distribute transaction prices on an immediate basis; (2) create a database of transactions in corporate bonds to enable regulators to take a pro-active role in supervising the corporate debt market; and (3) create a surveillance program, in conjunction with the development of a database, to better detect fraud and foster investor confidence in the fairness of the corporate debt market."[16] In response, the NASD prepared and proposed the TRACE Rule 6210 which, after a number of amendments, was approved by the SEC in January 2001.

In July 1, 2002, the NASD introduced TRACE, an automated system that accommodates reporting and dissemination of OTC transactions in eligible corporate debt securities.[17] All brokers/dealers registered with the SEC are mandated to report the transactions that they facilitate, as a principal or an agent, to TRACE shortly after execution. Reported information includes, among other things, the CUSIP number or FINRA symbol of the traded security, the

increases in relative importance of institutional investors who, the authors argue, prefer to avoid a public record of their large purchases and sales in part to reduce the risk of front-running.

[14] Such opacity is not necessarily a feature of dealer-oriented markets. For example, during our sample period, NASDAQ provided a greater level of both pre-trade and post-trade transparency.

[15] Matrix prices are algorithmically determined by adding a fixed spread to a frequently traded Treasury bond or by basing the price on bonds issued by similar firms (e.g., firms with similar credit ratings).

[16] See https://www.sec.gov/rules/sro/nd9965n.htm (last accessed on February 22, 2017).

[17] A TRACE-eligible security is a debt security that is (1) U.S. dollar-denominated, (2) issued by a U.S. or foreign private issuer, and (3) registered by the SEC or issued pursuant to Section 4(2) of the Securities Act of 1933 and purchased or sold pursuant to Rule 144A.

date and time of execution, the transaction price, yield and volume (in dollars of par), and a symbol indicating whether the transaction is a buy or sell.[18]

For all eligible corporate debt securities, transaction reporting to TRACE began immediately on July 1, 2002. However, the NASD implemented public dissemination in multiple phases because of the potential negative impact that dissemination could have on the liquidity of smaller, less actively traded issues, .[19] Figure 1 illustrates the implementation timeline (see Asquith et al. (2013) for additional details).

Phase I began on July 1, 2002 and required the dissemination of all transactions in investment grade bonds with an original issue size of $1 billion or greater, as well as 50 actively traded high yield bonds which were carried over from the NASD's Fixed Income Pricing System (FIPS). By the end of 2002, transactions on 520 securities were being disseminated by TRACE. Phase II was implemented on March 3, 2003 and expanded public dissemination to include all bonds rated A- or better with an original issue size of at least $100 million. An additional 120 BBB rated bonds with issue sizes less than $1 billion are added as part of Phase II in April 2003.[20] With the implementation of Phase II, the number of disseminated bonds increased to 4,650. The last phase of TRACE was implemented in two stages. Phase IIIA became effective on October 1, 2004 and initiated transaction reporting in 9,558 new bonds rated BBB- or better. Phase IIIB became effective on February 7, 2005 and initiated dissemination for 3,016 new bonds rated BB+ or lower.[21] According to the NASD, TRACE began disseminating 99% of all the transactions in eligible corporate debt securities after the completion of Phase III. In March 2010, FINRA publicly released an Enhanced TRACE data set that includes all disseminated and non-disseminated historical transactions. This data set allows us to examine the effect of dissemination at a given point in time, by comparing bonds with and without disseminated transactions.[22]

[18]The time delay to report a transaction was initially 75 minutes. NASD reduced it to 45 minutes on October 1, 2003, to 30 minutes on October 1, 2004, and to 15 minutes on July 1, 2005. Since January 9, 2006, all transactions are reported immediately after execution.

[19]Dissemination could reduce dealers' willingness to commit capital to risky or illiquid securities by reducing spreads and by making it more costly to unwind inventory after a large trade.

[20]Goldstein et al. (2007) use these 120 BBB-rated bonds and a control sample of non-disseminated bonds to examine the effect of dissemination on liquidity.

[21]As part of Phase IIIB, dissemination of transactions with a dollar volume exceeding $1 billion in infrequently traded high yield securities were subject to delay.

[22]The types of securities subject to TRACE reporting and dissemination have increased over time. According to *TRACE Fact Book 2016*, on March 1, 2010, TRACE began reporting transaction data for all U.S. agency de-

2 Data

The data used in this paper come from a variety of different sources. We obtain information on bond ratings and other bond characteristics from Mergent's Fixed Income Securities Database (FISD); secondary market bond transaction data from the Enhanced TRACE database (TRACE); the dissemination phase of each bond from the Financial Industry Regulatory Authority (FINRA, formerly NASD); daily stock returns from the Center for Research in Security Prices Daily Stock files (CRSP); monthly S&P long-term issuer ratings, the date of quarterly earnings announcements, and quarterly firm financials from Compustat - Capital IQ North America (Compustat); analyst earnings forecasts from I/B/E/S Summary History files (IBES); credit default swap indicators from Bloomberg; information on firm 8-K, 10-Q, and 10-K filings from the Securities and Exchange Commission's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system; and daily Treasury constant maturity rates as well as the monthly Consumer Price Index (CPIAUCSL) from FRED. We provide descriptions of the samples based on these data in subsequent sections, and variable definitions in Table A1.

3 Short-Term Price Impact of Rating Downgrades

In this section, we examine the effect of dissemination on the informational value of credit ratings by comparing the average short-term stock (and bond) price reaction to announcements of rating downgrades before and after dissemination.

3.1 Sample

Our event study sample consists of 1,803 downgrades of corporate bond ratings (involving 614 unique issuers) by S&P, Moody's, and Fitch (commonly referred to as the Big Three Nationally Recognized Statistical Rating Organizations (NRSRO)). Our sample period is between July 1, 2001 and February 7, 2006. Data on rating downgrades and bond characteristics come from

bentures. Since May 16, 2011, TRACE is collecting transactions in asset-backed and mortgage-backed securities. However, only transactions in agency pass through mortgage-backed securities (to-be-announced and specified pool transactions) are currently subject to dissemination. On June 30, 2014, transactions in SEC Rule 144A bonds became subject to dissemination. See http://www.finra.org/sites/default/files/2016-trace-fact-book.pdf (last accessed on March 15, 2017).

FISD. A number of recent papers, including Jorion et al. (2005) and Chava et al. (2016), use the same database to examine the stock price impact of bond rating revisions.

We restrict our sample to dollar-denominated U.S. corporate debentures, medium-term notes, strips, zero coupon bonds, U.S. bank notes, and retail notes without any credit enhancements.[23] We eliminate bonds with missing original amount, offering date, or scheduled maturity date and require sample bonds to have at least one TRACE transaction record. When ratings on multiple outstanding bonds of an issuer are revised on the same day, we count the event only once and use the characteristics of the bond with the maximum absolute numerical rating change. We also condition the sample on the availability of sufficient stock return data in CRSP to calculate the impact of the rating downgrade on the issuer's stock price. Finally, to reduce the potential influence of outliers on our results, we trim the top and bottom 1% of the downgrades based on their stock price impact.

3.2 Distribution of Rating Downgrades

Table 1 provides the quarterly frequency distribution of rating downgrades in our event study sample. We present the results separately for the overall sample (left panel, N=1,803), the subsample of issuers with disseminated bonds (middle panel, N=702), and the subsample of issuers without disseminated bonds (right panel, N=1,101). As shown, about a third of the downgrades in the full sample occur during the first four quarters of our sample period (before the introduction of TRACE). The clustering of downgrades in this period reflects, in part, the recession between March and November 2001—downgrades tend to increase sharply towards the end of recessions (Amato and Furfine, 2004). As shown in the middle panel, the fraction of downgrades for issuers with disseminated bond transactions increases over time; the number spikes around the implementation date of each dissemination phase. The sample was constructed such that none of the downgrades in the first four quarters of our sample period are in the dissemination subsample, and all of the downgrades in the last four quarters of the sample period are in the dissemination subsample.

[23] Following the past literature, we eliminate Rule144A private placements, convertible bonds, perpetual bonds, asset-backed bonds, mortgage backed bonds, secured lease obligations, exchangeable bonds, foreign currency bonds, and Yankee bonds.

3.3 Mean Characteristics of Downgrades by Dissemination

Table 2 provides a comparison of the mean characteristics of downgrades for the subsamples of issuers with and without disseminated bonds. The list of variables in the table include (i) variables that have been shown by past studies to affect the price impact of rating downgrades, and (ii) variables that either affect or reflect the timing of TRACE dissemination. Detailed descriptions of the variables are available in Panel A of Table A1.

Since the fraction of issuers with disseminated bonds increases during the TRACE implementation window, any variable that exhibits a positive time trend over the same period will have a significantly higher mean in the dissemination subsample than in the non-dissemination subsample. There are three such variables in Table 2: the CDS reference entity dummy, the contaminated announcement dummy, and the negative watch dummy.

The proportion of downgrades in our sample involving CDS reference entities increases monotonically from 46% in 2001 to 83% in 2005, reflecting the rapid growth of the CDS market during this period. The fraction of contaminated announcements—i.e., downgrades that coincide with earnings announcements or the filing of an annual 10-K, quarterly 10-Q, or current 8-K report with the SEC—increases by about 20% in the second half of our sample period. The increase arises from a dramatic increase in the number of 8-K reports filed after August 23, 2004 when the SEC expanded the list of events that are reportable on Form 8-K.[24] Finally, the proportion of downgrades preceded by a negative watch jumps from 16% in 2001 to 66% in 2002 (and remains stable afterwards), presumably in response to criticisms after the Enron scandal that rating agencies are too slow to inform the market about changes in the riskiness of rated companies. Overall, the proportion of CDS reference entities, contaminated announcements, and negative watches is 30%, 15%, and 20% higher, respectively, in the dissemination subsample than in the non-dissemination sample.

Earlier dissemination of a particular bond, ceteris paribus, increases the likelihood that a downgrade will occur after dissemination. Therefore, variables that are positively (negatively) correlated with early dissemination will have higher (lower) means in the dissemination subsample than in the non-dissemination subsample. For example, as shown in Table 2, the

[24] See: https://www.sec.gov/rules/final/33-8400.htm.

proportion of Phase II firms is significantly higher and the proportion of Phase IIIB firms is significantly lower in the dissemination subsample than in the non-dissemination sample. Moreover, a relatively higher fraction of issuers in the dissemination subsample have investment grade ratings, reflecting, in part, the fact that dissemination began earlier for investment grade bonds.

Among the remaining two variables in the table, the average size of the ratings change is about 1.5 notches in both subsamples, and the average number of days since the last downgrade is comparable as well. Overall, Table 2 offers an important takeaway: to identify the causal effect of dissemination on our outcome variables, it is important to control for time trends and for factors that affect the timing of dissemination decisions.

3.4 Abnormal Stock Returns around Downgrades: Univariate Results

To calculate cumulative abnormal daily stock returns associated with rating downgrades, we first estimate the β coefficients for each stock i using the following regression model:

$$R_{i,t} = \alpha_i + \beta_{M,i} MktRf_t + \beta_{SMB,i} HML_t + \beta_{HML,i} HML_t + \beta_{UMD,i} UMD_t + \epsilon_{i,t} \tag{1}$$

Here, $MktRf$, SMB, HML, and UMD are the return benchmark factors due to Fama and French (1993) and Carhart (1997). They are, respectively, the excess return on the market portfolio over the risk-free rate, the return on small-minus-big firms, the return on high-minus-low book-to-market ratio firms, and the return on winner-minus-loser stocks. The estimation window is trading days (-251, -31) where day 0 is the date of rating downgrade. If the downgrade occurs on a non-trading day, day 0 is the first subsequent trading day.

In the second step, we calculate the abnormal stock return for stock i on day t as:

$$AR_{i,t} = R_{i,t} - \left[\widehat{\alpha_i} + \widehat{\beta_{M,i}} MktRf_t + \widehat{\beta_{SMB,i}} HML_t + \widehat{\beta_{HML,i}} HML_t + \widehat{\beta_{UMD,i}} UMD_t\right] \tag{2}$$

Finally, we calculate the cumulative abnormal return (CAR_i) for a stock as the sum of the $AR_{i,t}$ values during the three trading days centered on the date of downgrade (the event window). We require at least 63 non-missing returns to estimate Equation 1 and three non-missing returns in the event window to calculate CAR_i.[25]

Figure 2 presents the quarterly averages of the cumulative abnormal stock returns over our sample period. Until the introduction of TRACE, the average abnormal returns are negative and exhibit a downward trend (they become bigger in absolute value). After the introduction of TRACE, they exhibit an upward trend. The reversal in the trend around the introduction of TRACE means it is unlikely that the estimated effect of dissemination is coincidental. The average abnormal returns converge to zero as the fraction of disseminated transactions converge to one; in other words, when all transaction information is publicly dissemination, rating downgrades become less informative. The average abnormal returns remain stable at about 0% for at least a year after the full implementation of TRACE.

Table 3 provides a univariate analysis of the abnormal returns in the cross-section. Panel A presents the results for the full sample of downgrades. As shown, the average abnormal return is -3.71% for issuers in the non-dissemination group and -0.85% for issuers in the dissemination group; both averages are significantly different from zero at the 1% level. The difference between the two averages, which represents the estimated effect of dissemination, is 2.86% (significantly different from zero at the 1% level), indicating that dissemination reduces the stock price impact of rating downgrades by more than 75%.

Because we trim the top and bottom 1% of the observations, these results are unlikely to arise from the influence of outliers on the means. This is confirmed when we compare the median abnormal returns using the non-parametric Wilcoxon rank-sum test, as we continue to find a significant dissemination effect. Furthermore, we obtain similar results when we analyze standardized abnormal returns (or SCAR) to reduce a possible concern that the effect of dissemination could reflect cross-sectional differences in return volatility.[26]

As an additional robustness check, we remove observations that are contaminated by contemporaneous firm-specific news releases during the event window. Panel B displays our findings. As shown, the estimated effect of dissemination in this sample is almost identical

[25] Our results are not sensitive to the selection of the estimation window, event window, or the benchmark pricing model. Throughout the paper, we report the cross-sectional standard errors of the abnormal returns. All our results are robust to accounting for time-series or cross-sectional dependence in returns, consistent with the conclusion in Kothari and Warner (2007) that short-term event studies are not sensitive to assuming independence of abnormal returns. The robustness tests are available upon request.

[26] SCAR is computed as the cumulative abnormal return scaled by the daily estimation window residual stock return volatility times the square root of three (the number of trading days in the event window).

(2.64%) and statistically significant at the 1% level. Moreover, in this subsample, the average abnormal stock return is indistinguishable from zero for issuers with disseminated bonds, suggesting that the average downgrade is uninformative when bond prices are readily available to investors. Overall, the evidence presented in Table 3 is consistent with the view that dissemination of bond prices reduces the relevance of credit ratings.

3.5 Abnormal Stock Returns around Downgrades: Multivariate Results

We next estimate the effect of dissemination on announcement returns using a regression framework where we control for variables that have been shown in past studies to affect the stock price reaction to rating downgrades. In some specifications, we also include year-quarter fixed effects and firm fixed effects to mitigate a possible concern that dissemination could merely be a proxy for unobserved time trends or time-invariant firm-specific factors that are correlated with the informativeness of ratings revisions.

Table 4 provides our findings. The dependent variable is the three-day cumulative abnormal stock return (in percentages). All the regressions are estimated via ordinary least squares (OLS). The standard errors of the regression coefficients are heteroskedasticity-consistent and clustered by firm.[27] Column 1 presents a univariate specification. In this column, the estimated coefficient of dissemination is identical to the univariate estimate reported in Panel A of Table 3 and serves as a benchmark for the multivariate specifications.

In addition to the dissemination dummy, the model presented in column 2 includes variables used in past studies that examine the stock price impact of rating downgrades. For example, we include the three variables that Jorion et al. (2005) include in their base regression models: an investment grade dummy (measured at the issuer level, at the end of the month before the month of downgrade), the size of rating change (in number of $\pm$ notches), and the natural logarithm of the number of days since the last rating downgrade by another rating agency. As shown, the estimated coefficient of the investment grade dummy is positive and statistically significant, suggesting that downgrades of investment grade bonds cause smaller stock price declines, a finding consistent with the fact that a one notch rating downgrade for investment grade bonds indicates a smaller change in expected default probability than the

[27]The results are robust to double clustering the standard errors at the firm and year-quarter level.

same size downgrade for high yield bonds. We also find that bigger changes in ratings result in bigger declines in stock prices, on average. Moreover, we find that the coefficient of the variable, days since last downgrade, is positive and significant, consistent with the view that, when there are big time gaps between rating changes, the information contained in the new rating is preempted by other news events.

Column 2 also includes indicators for other potentially relevant controls: whether the issuer was put on negative credit watch before the downgrade, whether the issuer is a CDS reference entity, and whether there were any confounding news announcements in the event window. Boot, Milbourn, and Schmeits (2006) predict that rating changes for an issuer on negative credit watch will be more informative than rating changes for issuers not on a credit watch. However, we find no significant relation between being on negative watch and the stock price impact of downgrades—a finding consistent with the empirical evidence in Chan, Faff, Hill, and Scheule (2011). The CDS dummy is included because Chava et al. (2016) find that the impact of rating downgrades on stock prices is considerably lower for CDS reference entities. The coefficient estimate of the CDS dummy in column 2 is positive and both statistically and economically significant, consistent with the evidence in Chava et al. (2016). Finally, the coefficient of the contaminated announcement dummy is negative and significant, suggesting that rating downgrades are more likely to coincide with negative news events about issuers than with positive news events. Including these additional control variables reduces the estimated effect of dissemination from 2.86% in column 1 to 2.43% in column 2 (or by about 15%), but does not change its significance level.

Column 3 contains all the variables in column 2, and adds dummy variables that indicate in which phase of the TRACE implementation the issuer's outstanding bonds began to have their trading information publicly disseminated. As shown, none of the phase dummies is statistically significant at conventional levels; this lack of significance mitigates concerns that the timing of dissemination could be based on the informativeness of credit ratings. The estimated effect of dissemination in column 3 is 1.94% (significant at the 1% level).

In column 4, we add year-quarter as well as industry (i.e., 1-digit SIC Code) dummies to the control variables in column 3, to address the concern that the dissemination dummy could be picking up time-series or cross-industry variation in unobserved factors correlated with the informativeness of rating downgrades. We find that the inclusion of time and industry fixed effects reduces the estimated effect of dissemination only slightly, from 1.94% to 1.61%, or by about 17%. By including time dummies, we attribute the time-series variation in announcement returns entirely to factors other than dissemination, and thereby possibly underestimating the overall effect of dissemination.

Finally, in column 5, we replace the industry fixed effects in column 4 with firm fixed effects to further mitigate the concern that dissemination is picking up unobserved time-invariant firm characteristics that are correlated with the informativeness of rating downgrades. Since phase dummies have almost no variation within firm, we drop them from the estimation. In our sample, 282 issuers were downgraded at least once before and once after dissemination. About half of the sample downgrades (894 observations) involve these 282 issuers. We estimate the firm fixed effects model using the full sample, and as shown in column 5, find that dissemination reduces the average stock price impact of rating downgrades by 3.29% (significant at the 1% level).[28] As a robustness check, we also restrict the estimation sample to downgrades involving the 282 firms, and find that the effect of dissemination is 2.29% and significant at the 1% level (not tabulated).

We next estimate the same regression specifications as in Table 4 (i) using non-contaminated observations, or (ii) replacing the dependent variable, CAR, with standardized CAR (or SCAR), and obtain similar results, as shown in Table 5. Overall, the results in Tables 4 and 5 suggest that the dissemination of bond transactions substantially reduces the stock price impact (or informativeness) of rating downgrades.

3.6 Abnormal Bond Returns around Downgrades

It is possible that the decline in the average stock price reaction to rating downgrades after dissemination occurs because downgrades in this era have positive implications for stockholders. According to Goh and Ederington (1993), while an unanticipated downgrade is unequivocally bad news for bondholders, it is not always bad news for stockholders: Information that negatively affects the value of the firm's assets reduces both the bond and stock value, but information that increases the variance of the firm's asset value increases stock prices and

[28]When we include the phase dummies, the estimated coefficient of dissemination becomes 3.49% (t-stat = 4.33)

decreases bond prices. For example, if the rating is downgraded because the rating agency anticipates a leverage increase that will shift wealth from bondholders to stockholders, bond prices are likely to fall, but equity prices should rise. To address this possibility, we also examine the effect of dissemination on abnormal *bond* returns.

Our data on bond returns comes from the Enhanced TRACE database. Using an algorithm provided by Dick-Nielsen (2014), we eliminate canceled, corrected, and reversed transactions, as well as double-counted inter-dealer transactions from TRACE. As suggested by Bessembinder, Kahle, Maxwell, and Xu (2009), we eliminate all trades under $100,000; using the remaining trades, we calculate the daily trade-weighted price by weighting each intra-day trade by its size. We calculate daily bond returns using clean prices which do not include accrued interest.[29] We calculate abnormal bond returns as follows. We begin with the return on an individual bond (the "target bond"). From the return on the target bond, we subtract the return on a value-weighted index of bonds; for each target bond in our sample, we construct the corresponding index from daily TRACE data of all bonds that have the same credit rating (measured as the worst across all three agencies without $\pm$ notches) whose ratings do not change within a 30-day window centered on the downgrade of the target bond. We cumulate the abnormal returns over the three-day event window. We eliminate bonds with missing daily returns during the event window. We calculate firm-level abnormal bond returns as the weighted average abnormal return across all outstanding bonds of an issuer; the weights are based on the remaining outstanding amounts of individual bonds relative to the outstanding amounts of all downgraded bonds of the issuer.

Compared to our stock return sample, our bond return sample has some limitations. Because TRACE data are available only after 2002, our sample period for the abnormal bond return analysis is one year shorter than the sample period for the abnormal stock return analysis. Also, we lose observations since bonds are infrequently traded and a significant fraction of sample bonds are not traded during the entire event window. Moreover, we do not include Phase I bonds in our sample since we cannot calculate abnormal bond returns associated with their pre-dissemination downgrades. Our estimation sample consists of 402 observati-

[29] Bessembinder et al. (2009) find that excluding accrued interest has a negligible effect on the power of empirical tests designed to estimate short-term abnormal bond returns.

ons (141 downgrades where the issuer has no disseminated bonds and 261 downgrades where transactions of at least one of the downgraded bonds are disseminated).

In univariate tests (not tabulated), we find that dissemination increases the average (median) abnormal value-weighted bond return from -4.44% to -1.12% (-1.63% to -0.58%). The average (median) effect of dissemination is 3.32% (0.57%) and is economically large and statistically significant at the 1% level. Table 6 presents our regressions. Specifications in columns 1 to 5 are identical to the respective specifications in Table 4. As shown, the effect of dissemination is statistically significant in all the specifications except for the firm fixed effect specification in column 5, where the coefficient is economically large (1.92%) but not statistically significant at conventional levels (t-stat $= 1.32$). The lack of significance presumably arises from the relatively small size of the estimation sample. Overall, the evidence in 6 reinforces the view that public dissemination of transaction prices reduces the relevance of credit ratings as a source of information.

3.7 Dissemination or Reduced Confidence in Ratings?

Bar-Isaac and Shapiro (2013) model the reputational costs of providing lower quality ratings for issuer-paid rating agencies and predict that ratings quality will be lower during economic booms than during recessions.[30] If investors recognize that the quality of ratings changes across the business cycle, their model could offer an alternative explanation for why the price impact of rating downgrades falls during the later part of our sample period, when the U.S. economy was expanding. We believe the inclusion of year-quarter fixed effects in our regression models mitigates a possible concern that the estimated effect of dissemination reflects time-series changes in ex ante ratings quality (or reduced confidence in ratings). Nonetheless, we employ two empirical tests designed to examine this issue directly.

First, we examine how dissemination affects the price impact of downgrades from an investor-paid rating agency, Egan-Jones Ratings (EJR). Since EJR is compensated by investors, not by issuers, the quality of its ratings should be less susceptible to economic cycles as long as investors' demand for accurate ratings is relatively stable. Therefore, we would

[30]They characterize economic booms by low overall default probabilities and tighter competition in the labor market for qualified credit analysts.

not expect to find different market reactions to EJR downgrades of disseminated and non-disseminated firms unless dissemination reduces the incremental informativeness of credit ratings.

Unlike the Big Three issuer-paid rating agencies, EJR does not rate individual bonds but solely provides issuer (or firm-level) ratings. During our sample period, there are 847 rating downgrades by EJR involving one of the issuers in our main event study sample. As shown in Table 7, using the same regression framework as in Table 4 and the sample of 847 downgrades, we find that dissemination reduces the stock price impact of EJR downgrades by between 3.0% and 4.9% (significant at the 5% level or higher). These results are inconsistent with the view that dissemination serves as a proxy for reduced investor confidence in issuer-paid ratings during economic booms.

Second, we examine the market reaction to downgrades of bank loan ratings by S&P using ratings data obtained from the S&P RatingXpress database. If investors have less confidence in issuer-paid ratings during the second half of our sample period, we would expect the average market reaction to S&P downgrades to fall in this period for both bonds and bank loans. However, as shown in Figure 3, using 338 downgrades of loan ratings where the issuer had no outstanding bonds subject to TRACE reporting, we find that the annual average stock price impact of downgrades of bank loans by S&P becomes slightly bigger (not smaller) in 2004 and 2005. Finding no significant time-series reduction in the informativeness of rating downgrades for a group of issuers not treated by dissemination increases our confidence that we estimate the "true" effect of dissemination in Tables 4, 5, and 6.

Finally, while not tabulated, we also examine the stock price reaction to loan rating downgrades for 122 issuers with outstanding bonds subject to TRACE reporting. In 70 cases where transactions in the issuer's bonds are publicly disseminated, the average abnormal stock return associated with the loan rating downgrade is -1.97% (significant at the 10% level). In the remaining 52 cases where bond transactions are not disseminated, the average abnormal stock return is -12.55% (significant at the 1% level). The difference is 10.58% and is economically large and statistically significant at the 1% level. The evidence suggests dissemination reduces the price impact of both bond and loan rating downgrades.

3.8 Cross-Sectional Variation in the Effect of Dissemination

In this section, we examine how the effect of dissemination on the informativeness of credit ratings varies with various issuer characteristics. Our main hypothesis is that dissemination will matter less for rating informativeness where there is less uncertainty regarding the credit risk of the issuer or where alternative market-based signals of firm credit risk are available. For example, we would expect dissemination to matter less where the issuer is a CDS reference entity, where the issuer has outstanding bonds traded on an organized exchange, or where stock analysts provide reliable forecasts of the issuer's future earnings (e.g., where analyst forecast dispersion and forecast error are low). We would also expect dissemination to matter less for issuers with an investment grade rating. This is partly because credit risk is a small component of the observed credit spreads for those firms (Huang and Huang, 2012), and partly because there is a strong correlation between an investment grade rating and the availability of alternative market-based measures of credit risk information.

Table 8 presents our findings. Each row in the table includes a separate regression. The dependent variable is the three-day cumulative abnormal stock return associated with the rating downgrade (in percentages). Each regression includes a dissemination dummy, an information measure (e.g., CDS trading dummy), the interaction between the dissemination dummy and the information measure, all the control variables in column 2 of Table 4 (except for the CDS dummy which we include only in row 1) as well as year-quarter fixed effects and industry fixed effects. To facilitate the interpretation of the coefficient estimates, we use binary information measures. For example, low analyst forecast dispersion is a binary variable that equals one if analyst forecast dispersion is below the sample median. We define the binary variables low analyst forecast error and high stock liquidity in the same way. For presentation purposes, we only report the coefficient estimates and t-statistics associated with the dissemination dummy, information measures, and the corresponding interaction terms.

Overall, we find that the informativeness of credit ratings is less affected by dissemination if there are already market-based sources of information available: if the issuer is a CDS reference entity or if it has an exchange-traded bond or a highly liquid common stock. However, dissemination still has an effect even when market-based sources of information are available. For example, dissemination significantly reduces the informativeness of rating downgrades even for CDS reference entities. The average effect of dissemination is 3.82% when the issuer is *not* a CDS reference entity (significant at the 1% level), and 1.69% if the issuer is a CDS reference entity (significant at the 5% level). The difference in the effect of dissemination between the two groups is 2.13% and is statistically significant at the 5% level.

We also find that dissemination has no discernible effect on the informativeness of credit ratings when stock analysts are able to predict the issuer's future earnings with high accuracy and when analysts agree in their future forecasts. Finally, as conjectured, we find that the effect of dissemination is considerably bigger (i.e., by about 3.78%) for issuers rated below investment grade by S&P than for investment grade rated issuers. Overall, the evidence in Table 8 suggests that credit spreads are a more valuable source of information where reliable market-based measures of credit risk are unavailable.

4 Information Flow between Bond and Equity Markets

To formally test whether stock investors learn from bond prices (e.g., whether they update their beliefs about credit risk by observing publicly disseminated bond prices), we construct a daily panel of stock and bond returns, using issuers included in our main event study sample. The sample consists of 107,672 pairs of daily stock and value-weighted bond returns during July 2, 2002 and February 7, 2006 (447 unique firms and 908 unique trading days). All issuers included in our daily panel have available bond returns both before and after dissemination. We eliminate all trading days with missing bond returns (the returns are available only if the bond trades on two consecutive trading days). Moreover, to reduce the possible influence of TRACE data entry errors and large outliers on our results, we eliminate observations that are in the top and bottom 1% of the daily bond return distribution.

Following Das, Kalimipalli, and Nayak (2014), who examine the flow of information between CDS, bond, and stock markets, we define the return on each bond issue as the daily change in average daily yields (weighted by trade size), multiplied by -1. We calculate firm-level daily bond returns as described in Section 3.6.

Our analysis is based on a methodology proposed by Kwan (1996).[31] Our baseline specification is shown in Equation 3:

$$Ret^B_{i,t} = \beta_0 + \beta_1 Ret^E_{i,t+1} + \beta_2 Ret^E_{i,t} + \beta_3 Ret^E_{i,t-1} + \epsilon_{i,t} \tag{3}$$

Here, $Ret^B_{i,t}$ is the market value-weighted bond portfolio return for firm i on trading day t. $Ret^E_{i,t}$ is the contemporaneous common stock return, $Ret^E_{i,t+1}$ and $Ret^E_{i,t-1}$ are the lead and lagged daily stock returns, and $\epsilon_{i,t}$ is the error term. All the returns are in percentages. In this equation, β_1 shows the flow of information from the bond market to the equity market, and β_3 shows the information flow from the equity market to the bond market. Our main hypothesis is that β_1 is greater when bond transactions are publicly disseminated, especially before rating downgrades which tend to follow adverse changes in credit risk.

Table 9 presents our findings. The table provides coefficient estimates as well as t-statistics based on heteroskedasticity-consistent standard errors that are double clustered by issuer and date (in parentheses). In column 1, we estimate Equation 3 for the full sample of daily returns and find that there is a two-sided flow of information between equity and bond markets (both β_1 and β_3 are significantly greater than zero), but that more information flows from the equity market to the bond market than vice versa ($\beta_1 > \beta_3$). In column 2, we include an interaction of each variable in column 1 with the dissemination dummy to examine how dissemination affects the information flows. The coefficient of $Ret^E_{i,t+1}$ in this column suggests that, before dissemination, there was no significant flow of information from the bond market to the equity market. Moreover, the coefficient of $Dissemination \times Ret^E_{i,t+1}$ indicates a significant increase in information flow to the equity market from the bond market after dissemination, a finding that is consistent with stock investors learning from transparent bond prices.

In columns 3 and 4, we split the sample into two, based on whether or not a bond rating downgrade is recorded by FISD in the next 30 trading days.[32] As shown in column 3, the coefficient of $Dissemination \times Ret^E_{i,t+1}$ increases dramatically, from 0.20 to 0.57, in the subsample of trading days preceding a rating downgrade. This suggests that the information flow

[31] Hotchkiss and Ronen (2002) examine the informational efficiency of the corporate bond market relative to the equity market, using a small sample of high yield bonds whose prices were disseminated through the fixed income pricing system (FIPS) and find that stocks do not lead bonds in reflecting firm specific information.

[32] The results are similar if we use 90 days instead of 30 days.

from the bond market to the equity market is particularly pronounced before important rating events. Indeed, as shown in column 4, for trading days not followed by a rating downgrade, there is no significant flow of information from the bond market to the equity market.

5 Information Content of Ratings and Spreads

In this section, we examine how dissemination affects the relation between credit ratings and credit spreads as well as the ability of both variables to predict default, using a monthly panel data.

5.1 Sample

In our estimations, we use a monthly panel data set which consists of 27,167 observations (561 unique firms and 56 unique months). The sample period is between July 2001 and February 2006. The sample is restricted to issuers in our event study sample, and includes only issuers with both disseminated and non-disseminated historical bond transactions in TRACE. We exclude firm-months in which the issuer rating is missing or worse than CC, C, SD (selective default), and D (default). Our analyses involving credit spreads are based on a subsample of 20,954 observations (558 unique firms and 44 unique months) since credit spreads are available only after the introduction of TRACE in July 2002 and only for issuers with fixed rate bonds. In specifications controlling for firm financial characteristics, we lose additional observations due to missing quarterly Compustat data.

5.2 The Relation between Credit Ratings and Credit Spreads

We hypothesize that credit ratings become more sensitive to the level and changes in credit spreads after dissemination for two reasons. First, just like stock and bond investors, credit rating agencies might learn from transparent bond prices and incorporate this additional information into their rating models. Second, transparent bond prices might make it easier for investors to detect inflated issuer-paid ratings, which in turn could elevate rating agencies' reputational concerns. Our first test of this hypothesis involves estimating the contemporaneous correlation between credit ratings and credit spreads using Equation 4:

$$\begin{aligned} LN(Rating_{i,t}) = &\alpha + \beta_1 Spread_{i,t} + \beta_2 Dissemination_{i,t} \\ &+ \beta_3 Spread_{i,t} \times Dissemination_{i,t} + \gamma \times Z_{i,t} + \nu_i + \kappa_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

The unit of observation is a firm-month. The dependent variable is the natural logarithm of the S&P long-term issuer rating converted to numeric scale such that a lower numeric rating indicates a higher likelihood of default (CC (1), CCC- (2),..., AA+ (19), AAA (20)).[33] We use the natural logarithm of the ratings because a one unit rating change has a bigger effect on the likelihood of default (and credit spreads) at lower ratings. $Spread$ is the monthly firm-level trade-weighted average credit spread. Z is a matrix of firm characteristics including a CDS reference entity indicator. Definitions of $Spread$ and all other control variables are provided in Panel B of Table A1. $Dissemination$ is an indicator variable that equals one if transactions in the issuer's outstanding bonds are publicly dissemination via TRACE. ν_i and κ_t indicate firm and year-month fixed effects, respectively. β_1 shows the (conditional) correlation between credit ratings and credit spreads prior to dissemination. β_3 shows the effect of dissemination on this correlation (or the treatment effect). We estimate Equation 4 using OLS. To allow for correlations among different firms in the same month and different months in the same firm, we double cluster regression standard errors by firm and year-month. The standard errors are also heteroskedasticity-consistent.

Table 10 presents the results. In column 1, we report a parsimonious model that includes only three explanatory variables: $Spread$, $Dissemination$, and $Spread \times Dissemination$. In column 2, we saturate our model with firm and year-month fixed effects as well as firm financial characteristics for additional identification. We find in both specifications that dissemination significantly increases the correlation between credit ratings and credit spreads. For example, based on coefficient estimates in column 2, the sensitivity of ratings to credit spreads more than doubles after dissemination ($\beta_1 = -0.70$ and $\beta_3 = -1.10$). The estimated effect of dissemination is unlikely to arise from reverse causality since we show in Table 6 that dissemination significantly reduces the effect of rating downgrades on bond prices.

[33] We use firm-level ratings because our data set is at the firm level and default is generally a firm-level event. Our results are robust to using bond-level ratings.

We next estimate the responsiveness of rating *changes* (i.e., the likelihood of rating downgrades or upgrades) to *changes* in credit spreads using Equation 5:

$$\begin{aligned}\Delta Rating_{i,t} =& \alpha + \theta_1 \Delta Spread_{i,t} + \theta_2 Dissemination_{i,t} + \theta_3 \Delta Spread_{i,t} \times Dissemination_{i,t} \\ & + \theta_4 \Delta Spread_{i,t-1} + \theta_5 Dissemination_{i,t-1} + \theta_6 \Delta Spread_{i,t-1} \times Dissemination_{i,t-1} \\ & + \phi \Delta Z_{i,t} + \kappa_t + \epsilon_{i,t}\end{aligned} \tag{5}$$

Here, $\Delta Spread_{i,t} = Spread_{i,t} - Spread_{i,t-1}$. The main coefficients of interest are θ_3 and θ_6, which show the sensitivity of rating actions to contemporaneous and lagged changes in credit spreads, respectively.

Columns 3 and 4 of Table 10 present models that examine how changes in credit spreads affect the likelihood of rating downgrades. The specification in column 4 includes monthly changes in firm characteristics as well as year-month fixed effects while the parsimonious specification in column 3 does not. Nonetheless, the coefficient estimates reported in the two columns are almost identical, mitigating potential concerns about omitted variables bias. Overall, we find that rating downgrades become substantially more sensitive to contemporaneous and lagged changes in spreads after dissemination. For example, dissemination more than doubles the likelihood of a downgrade in month t after an increase in average credit spreads during month t ($\theta_3 > \theta_1 > 0$). Moreover, dissemination increases the likelihood of a downgrade in month t by about 1.0% (or 53% at the mean), after a one standard deviation (0.83%) increase in credit spreads during month $t-1$.

Finally, in columns 5 and 6 of Table 10, we examine the sensitivity of rating *upgrades* to changes in credit spreads both before and after dissemination, using the same right-hand-side variables in columns 3 and 4. We find no evidence that rating upgrades become more (or less) sensitive to changes in credit spreads after dissemination.

Overall, our results are consistent with the hypothesis that credit ratings become more sensitive to credit spreads after dissemination through TRACE. Moreover, the asymmetry between rating downgrades and upgrades in terms of their responsiveness to changes in credit spreads after dissemination is consistent with the theoretical predictions of Piccolo and Shapiro (2016); they argue that more informative market trading makes rating inflation more transparent, and therefore increases the incentives for rating agencies to update ratings in a more timely manner.

5.3 The Ability of Ratings and Spreads to Predict Future Default

In our final set of empirical tests, we examine whether dissemination affects how well both credit spreads and credit ratings predict future defaults. If dissemination enhances the aggregation of default-relevant information in corporate debt markets, the predictive ability of spreads should increase after dissemination. Since ratings are more responsive to spreads after dissemination, improvements in the predictive ability of spreads would likely also produce improvements in the predictive ability of ratings. If we find evidence that ratings better predict future defaults after dissemination, that would help rule out the possibility that the smaller impact of rating downgrades on security prices after dissemination, documented in the first part of the paper, reflects a reduction in the quality of the ratings themselves.

Table 11 presents our default models. Regression standard errors are heteroskedasticity-consistent and clustered by both firm and year-month. The dependent variable, *Default*, is a binary variable that equals one if in the next two years (1) the issuer's long-term S&P rating or is downgraded to C, D, or SD, or (2) one or more of the issuer's bonds are downgraded to C or D by S&P, Moody's, or Fitch, according to FISD.[34] The average default rate in our sample is 1.21%.

In Panel A and B, we examine the predictive power of credit spreads and credit ratings, respectively. The models reported in column 1 include three explanatory variables: spread (or rating), dissemination dummy, and the interaction between the two variables. This specification allows us to examine the ability of spreads and ratings to predict default unconditionally. In column 2, we also include year-month and industry fixed effects as well as firm financial characteristics, and in column 3 we add phase fixed effects for additional identification. In all the models, the spread (rating) coefficient shows how well the spreads (ratings) predict future defaults pre-dissemination, and the coefficient of spread (rating) times dissemination shows how dissemination affects spreads' (ratings') predictive ability. If dissemination enhances the ability of spreads (ratings) to predict future default, we would expect the coefficient of the

[34] We obtain similar results using 1-year or 3-year defaults.

interaction term to be positive (negative) and statistically significant. As shown in Table 11, this is exactly what we find; the coefficients of both spread and rating more than double after dissemination.

In our final set of empirical tests, we compare the ability of credit ratings and credit spreads to predict future default by estimating three sets of default regressions via logit: (i) models that include the natural logarithm of end-of-month S&P long-term issuer ratings, (ii) models that include the average monthly credit spreads, and (iii) models that include both ratings and spreads. The estimation sample includes only issuer-months with non-missing spread data. The models include year-month fixed effects, but no additional controls.[35] When the predicted default probability from our logit models is greater than or equal to 0.5, we assume that the model predicts default. We then examine the predictive power of each model by comparing default predictions with actual defaults. False positives are cases in which the model predicts default, but the issuer does not default. True positives are cases in which the model predicts default and the issuer defaults. Since ratings provide ordinal rankings of issuers in terms of credit risk, we also calculate the cumulative accuracy ratio, which is based on a non-parametric receiver operating characteristics (ROC) analysis that examines how well ordinal rankings of firms by rating or credit spreads discriminates between firms that will and will not default.

Table 12 shows the estimation results for the full sample (left panel), pre-dissemination sample (middle panel), and post-dissemination sample (right panel). We have three main findings. First, we find that both credit spreads and credit ratings better predict default after dissemination. For example, the cumulative accuracy ratio of spreads (ratings) increases from 92.5% to 94.9% (from 85.2% to 93.4%) and the fraction of defaults correctly identified by spread-based (rating-based) models increases from 12.8% to 26.9% (2.6% and 15.4%). Second, spread-based default models are more accurate predictors of default than rating-based models both before and after dissemination; however, the former are also more likely to produce false positives. Third, in the post-dissemination period, a model that is based on both spreads and ratings is not only more accurate, on average, than a model based solely on credit spreads, but it also produces fewer false positives. Overall, these results appear to suggest that credit

[35]The results are robust to excluding the year-month fixed effects.

ratings and credit spreads are complementary sources of credit risk information. Future research that focuses on the default component of credit spreads and estimates the cost of false positives could provide a better assessment of the substitutability of credit ratings and credit spreads.

6 Conclusion

This paper examines how mandated price transparency in the secondary market for corporate bonds affects the information content of credit ratings. We have three main findings. First, we find that disseminating prices of completed trades dramatically reduces the effect of rating downgrades on security prices, especially where alternative market-based indicators of credit quality are unavailable. Second, we document that ratings become more sensitive to changes in credit spreads after dissemination. Finally, we find that dissemination enhances the ability of credit spreads to predict future defaults and increases the flow of information from the bond market to the equity market before important credit events, consistent with market prices playing their information aggregation and transmission roles more effectively in transparent markets. These results have implications for policy debates on mandated transparency regulations in OTC markets and the use of market-based indicators of credit risk as substitutes for credit ratings in financial regulation.

References

Amato, Jeffery D., and Craig H. Furfine, 2004, Are credit ratings procyclical?, *Journal of Banking and Finance* 28, 2641–2677.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ashcraft, Adam B., Paul Goldsmith-Pinkham, and James I. Vickery, 2010, MBS ratings and the mortgage credit boom, *FRB of New York Staff Report* No. 449.

Asquith, Paul, Thom Covert, and Parag Pathak, 2013, The effects of mandatory transparency in financial market design: Evidence from the corporate bond market, *NBER Working Paper Series* No. 19417.

Badoer, Dominique C., Cem Demiroglu, and Christopher James, 2017, Ratings quality and borrowing choice, Working paper, University of Florida.

Baghai, Ramin P., Henri Servaes, and Ane Tamayo, 2014, Have rating agencies become more conservative? Implications for capital structure and debt pricing, *Journal of Finance* 69, 1961–2005.

Bakke, Tor-Erik, and Toni M. Whited, 2010, Which firms follow the market? An analysis of corporate investment decisions, *Review of Financial Studies* 23, 1941–1980.

Bar-Isaac, Heski, and Joel Shapiro, 2013, Ratings quality over the business cycle, *Journal of Financial Economics* 108, 62–78.

Benmelech, Efraim, and Jennifer Dlugosz, 2010, The credit rating crisis, *NBER Macroeconomics Annual* 24, 161–208.

Bessembinder, Hendrik, Stacey E. Jacobsen, William F. Maxwell, and Kumar Venkataraman, 2016, Capital commitment and illiquidity in corporate bonds, Working paper, Arizona State University.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bessembinder, Hendrik, and William F. Maxwell, 2008, Transparency and the corporate bond market, *Journal of Economic Perspectives* 22, 217–234.

Bessembinder, Hendrik, William F. Maxwell, and Kumar Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds, *Journal of Financial Economics* 82, 251–288.

Biais, Bruno, and Richard C. Green, 2007, The microstructure of the bond market in the 20th century, Working paper, Carnegie Mellon University.

Bloomfield, Robert, and Maureen O'Hara, 2000, Can transparent markets survive?, *Journal of Financial Economics* 55, 425–459.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, *The Annual Review of Financial Economics* 4, 339–60.

Bond, Philip, and Itay Goldstein, 2015, Government intervention and information aggregation by prices, *Journal of Finance* 70, 2777–2812.

Boot, Arnoud W. A., Todd T. Milbourn, and Anjolein Schmeits, 2006, Credit ratings as coordination mechanisms, *Review of Financial Studies* 19, 81–118.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Chan, Howard, Robert Faff, Paula Hill, and Harald Scheule, 2011, Are watch procedures a critical informational event in the credit ratings process? An empirical investigation, *Journal of Financial Research* 34, 617–640.

Chava, Sudheer, Rohan Ganduri, and Chayawat Ornthanalai, 2016, Are credit ratings still relevant?, Working paper, Georgia Institute of Technology.

Chen, Jia, and Ruichang Lu, 2016, Pricing efficiency and market transparency: Evidence from corporate bond market, Working paper, Guanghua School of Management.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price, *Review of Financial Studies* 20, 619–650.

Cornaggia, Jess, and Kimberly J Cornaggia, 2013, Estimating the costs of issuer-paid credit ratings, *Review of Financial Studies* 26, 2229–2269.

Das, Sanjiv, Madhu Kalimipalli, and Subhankar Nayak, 2014, Did CDS trading improve the market for corporate bonds?, *Journal of Financial Economics* 111, 495–525.

Demiroglu, Cem, Julian R. Franks, and Ryan Lewis, 2016, Do market prices improve the accuracy of court valuations in Chapter 11?, Working paper, London Business School.

Diamond, Douglas W, 1985, Optimal release of information by firms, *Journal of Finance* 40, 1071–1094.

Diamond, Douglas W, and Robert E Verrecchia, 1981, Information aggregation in a noisy rational expectations economy, *Journal of Financial Economics* 9, 221–235.

Dichev, Ilia D., and Joseph D. Piotroski, 2001, The long-run stock returns following bond ratings changes, *Journal of Finance* 56, 173–203.

Dick-Nielsen, Jens, 2014, How to clean Enhanced TRACE data, Working paper, Copenhagen Business School.

Dimitrov, Valentin, Darius Palia, and Leo Tang, 2015, Impact of the Dodd-Frank Act on credit ratings, *Journal of Financial Economics* 115, 505–520.

Ederington, Louis H., Jess B. Yawitz, and Brian E. Roberts, 1987, The informational content of bond ratings, *Journal of Financial Research* 10, 211–226.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *Journal of Finance* 67, 933–971.

Edmans, Alex, Sudarshan Jayaraman, and Jan Schneemeier, 2016, The source of information in prices and investment-price sensitivity, Forthcoming, Journal of Financial Economics.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency, *Journal of Finance* 62, 1421–1451.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Flannery, Mark J., Joel F. Houston, and Frank Partnoy, 2010, Credit default swap spreads as viable substitutes for credit ratings, *University of Pennsylvania Law Review* 2085–2123.

Foucault, Thierry, and Laurent Fresard, 2014, Learning from peers' stock prices and corporate investment, *Journal of Financial Economics* 111, 554–577.

Goh, Jeremy C, and Louis H Ederington, 1993, Is a bond rating downgrade bad news, good news, or no news for stockholders?, *Journal of Finance* 48, 2001–2008.

Goldstein, Michael A., Edith S. Hotchkiss, and Erik R. Sirri, 2007, Transparency and liquidity: A controlled experiment on corporate bonds, *Review of Financial Studies* 20, 235–273.

Gopalan, Radhakrishnan, Yadav Gopalan, and Kevin Koharki, 2017, Market information and rating agency catering, Working paper, Washington University in Saint Louis.

Griffin, John M., and Dragon Y. Tang, 2012, Did subjectivity play a role in CDO credit ratings?, *The Journal of Finance* 67, 1293–1328.

Grossman, Sanford, 1976, On the efficiency of competitive stock markets where trades have diverse information, *Journal of Finance* 31, 573–585.

Grossman, Sanford, 1978, Further results on the informational efficiency of competitive stock markets, *Journal of Economic Theory* 18, 81–101.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Hand, John R.M., Robert W. Holthausen, and Richard W. Leftwich, 1992, The effect of bond rating agency announcements on bond and stock prices, *Journal of Finance* 47, 733–752.

Harford, Jarrad, Marc Martos-Vila, and Matthew Rhodes-Kropf, 2015, Corporate financial policies in overvalued credit markets, Working paper, University of Washington.

Hayek, Friedrich A., 1945, The use of knowledge in society, *American Economic Review* 35, 519–530.

He, Jie, Jun Qian, and Philip E. Strahan, 2012, Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities, *Journal of Finance* 67, 2097–2137.

He, Jie, Jun Qian, and Philip E. Strahan, 2016, Does the market understand rating shopping? Predicting MBS losses with initial yields, *Review of Financial Studies* 29, 457–485.

Hellwig, Martin F., 1980, On the aggregation of information in competitive markets, *Journal of Economic Theory* 22, 477–498.

Hite, Gailen, and Arthur Warga, 1997, The effect of bond-rating changes on bond price performance, *Financial Analysts Journal* 53, 35–51.

Holthausen, Robert W., and Richard W. Leftwich, 1986, The effect of bond rating changes on common stock prices, *Journal of Financial Economics* 17, 57–89.

Hotchkiss, Edith S., and Tavy Ronen, 2002, The informational efficiency of the corporate bond market: An intraday analysis, *Review of Financial Studies* 15, 1325–1354.

Huang, Jing-Zhi, and Ming Huang, 2012, How much of the corporate-treasury yield spread is due to credit risk?, *Review of Asset Pricing Studies* 2, 153.

Jankowitsch, Rainer, Giorgio Ottonello, and Marti G. Subrahmanyam, 2017, The new rules of the rating game: Market perception of corporate ratings, Working paper, Vienna University of Economics and Business.

Jiang, John Xuefeng, Mary Harris Stanford, and Yuan Xie, 2012, Does it matter who pays for bond ratings? Historical evidence, *Journal of Financial Economics* 105, 607–621.

Jorion, Philippe, Zhu Liu, and Charles Shi, 2005, Informational effects of regulation FD: Evidence from rating agencies, *Journal of Financial Economics* 76, 309–330.

Kothari, S.P., and Jerold B. Warner, 2007, Econometrics of event studies, in Espen Eckbo, ed., *Handbook of Corporate Finance: Empirical Corporate Finance*, 3–36 (Elsevier/North-Holland).

Kwan, Simon H., 1996, Firm-specific information and the correlation between individual stocks and bonds, *Journal of Financial Economics* 40, 63–80.

Luo, Yuanzhi, 2005, Do insiders learn from outsiders? Evidence from mergers and acquisitions, *Journal of Finance* 60, 1951–1982.

Marandola, Ginevra, and Rossella Mossucca, 2016, When did the stock market start to react less to downgrades by Moody's, S&P and Fitch?, Working paper, University of Bologna.

Partnoy, Frank, 1999, The Siskel and Ebert of financial markets: Two thumbs down for the credit rating agencies, *Washington University Law Quarterly* 77, 619–712.

Partnoy, Frank, 2006, How and why credit rating agencies are not like other gatekeepers, in Yasuyuki Fuchita, and Robert E. Litan, eds., *Financial gatekeepers: Can they protect investors?*, 59–102 (Brookings Institution Press).

Piccolo, Alessio, and Joel Shapiro, 2016, Credit ratings and market information, Working paper, Oxford University.

Vames, Stephan, 2003, NASD expands bond price reports—data on corporate issues become more transparent; market effects to be studied., *The Wall Street Journal* .

Weinstein, Mark I., 1977, The effect of a rating change announcement on bond price, *Journal of Financial Economics* 5, 329–350.

Xia, Han, 2014, Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?, *Journal of Financial Economics* 111, 450–468.

July 1, 2002 — **Introduction of TRACE (PHASE I)**

Transaction reporting: Investment grade bonds having an original issue size $1 billion or above, plus 50 high-yield bonds.

Time to report: 75 minutes

March 3, 2003 — **PHASE II**

Transaction reporting: Phase I bonds, plus all bonds rated A- or higher, if original issue size $100 million or above. Note: 120 BBB rated were bonds were added to Phase II bonds on April 14, 2003.

October 1, 2003 — **Time to report reduced to 45 minutes**

October 1, 2004 — **PHASE III-A**

Transaction reporting: All bonds with rating of BBB- or higher.

Time to report: Reduced to 30 minutes

February 7, 2005 — **PHASE III-B**

Transaction reporting: All bonds with rating of BB+ or lower.

July 1, 2005 — **Time to report reduced to 15 minutes**

January 9, 2006 — **Time to report revised to "Immediate"**

Figure 1. Timeline of TRACE Regulatory Changes
Information from FINRA's yearly TRACE Factbooks available on finra.org.

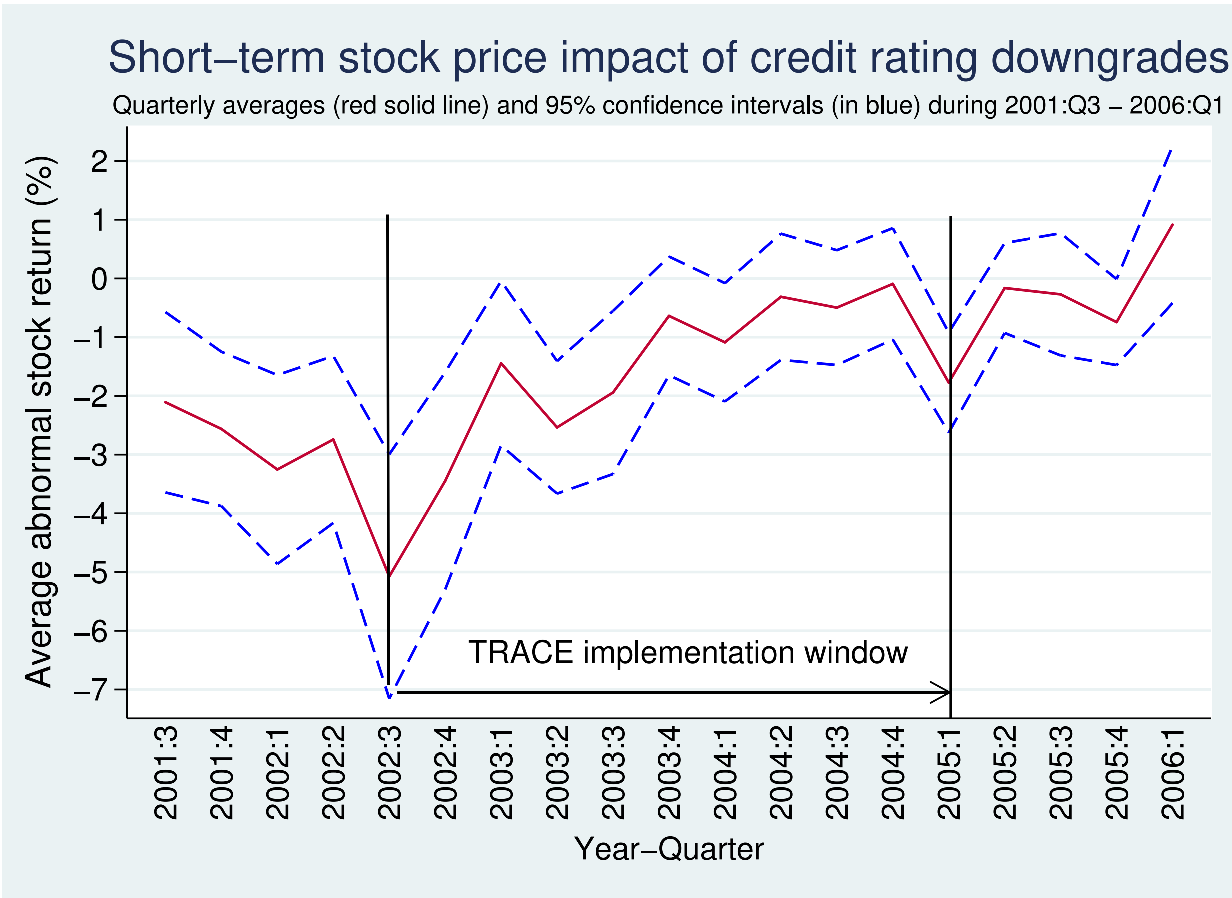

Figure 2. Quarterly average abnormal stock returns around rating downgrades
The sample consists of 1,803 corporate bond rating downgrades by Moody's, S&P, and Fitch during July 1, 2001 to February 7, 2006. The source of ratings data is Mergent's Fixed Income Securities Database (FISD). We count downgrades of multiple outstanding bonds of an issuer on the same day only once. If one rating agency upgrades the issuer's bonds while another one downgrades on the same day, we exclude the observation from our sample. We restrict our sample to downgrades of dollar-denominated corporate bonds, notes, and debentures issued by domestic U.S. public companies—we exclude downgrades of yankee bonds, bonds issued via private placements, perpetual bonds, preferred stocks, mortgage-backed bonds, secured-lease obligations, trust preferred securities, convertible bonds, and bonds with credit enhancements. The number of downgrades in each quarter is reported in Table 1. We use Carhart's Four-Factor Model as the benchmark pricing model to calculate abnormal stock returns. The event window is (-1, +1) trading days centered on the date of downgrade. The estimation window is (-251, -31) trading days. We require a minimum of 63 non-missing stock returns during the estimation window and three non-missing returns during the event window to include a downgrade in our sample.

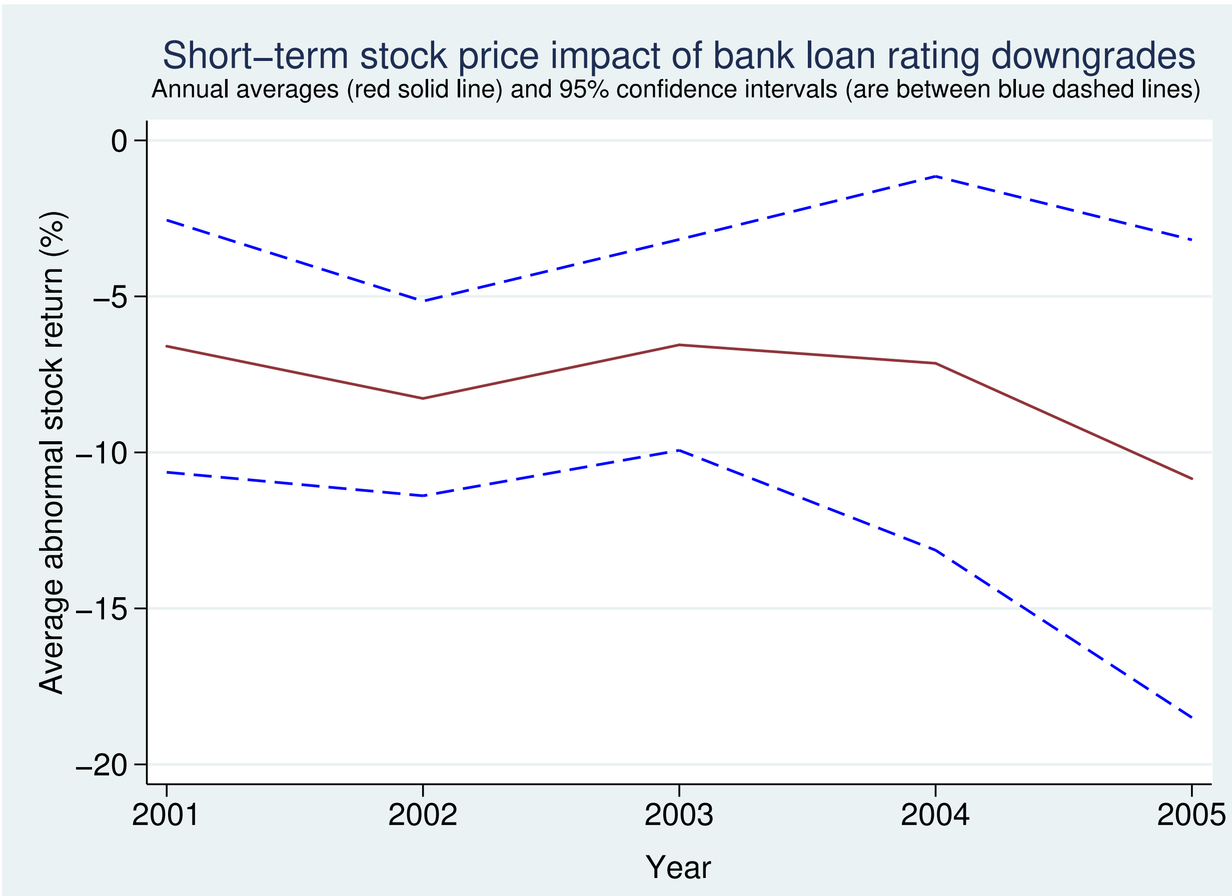

Figure 3. Annual average abnormal stock returns around loan rating downgrades
The sample consists of 338 downgrades of bank loan ratings by S&P from July 1, 2001 to December 31, 2005. The number of observations equals 80 in 2001, 113 in 2002, 72 in 2003, 34 in 2004, and 39 in 2005. The source of data on rating downgrades is S&P's RatingXpress database. We count downgrades of multiple outstanding loans of an issuer on the same day only once. We eliminate observations involving issuers that had publicly traded bonds subject to TRACE reporting. We further restrict the sample to dollar-denominated loans issued by domestic U.S. public companies. Unlike the bond-level analysis in Figure 2, the analysis here is at the annual level since the number of quarterly observations is too few to reliably calculate confidence intervals of average announcement returns. For the same reason, we do not plot the announcement returns associated with three downgrade events during January 1, 2006 to February 7, 2006. We calculate abnormal stock returns as described in Figure 2.

Table 1. Distribution of Sample Downgrade Events over Time

The sample consists of 1,803 corporate bond rating downgrades by Moody's, S&P, and Fitch during July 1, 2001 to February 7, 2006. The source of ratings data is Mergent's FISD. We count downgrades of multiple outstanding bonds of an issuer on the same day only once. If one rating agency upgrades the issuer's bonds while another one downgrades on the same day, we exclude the observation from our sample. We divide downgrades into two groups, "Dissemination" and "No dissemination", based on whether or not TRACE publicly disseminated transactions in any of the issuer's downgraded bonds during the (-31,-2) trading days before the downgrade event. Additional information on sample construction is available in Section 3.

	All		Dissemination			No dissemination		
Year-Quarter	N	Col %	N	Col %	Row %	N	Col %	Row %
2001-Q3	115	6.4	0	0.0	0.0	115	10.4	100.0
2001-Q4	163	9.0	0	0.0	0.0	163	14.8	100.0
2002-Q1	144	8.0	0	0.0	0.0	144	13.1	100.0
2002-Q2	146	8.1	0	0.0	0.0	146	13.3	100.0
2002-Q3	123	6.8	24	3.4	19.5	99	9.0	80.5
2002-Q4	152	8.4	47	6.7	30.9	105	9.5	69.1
2003-Q1	105	5.8	27	3.8	25.7	78	7.1	74.3
2003-Q2	104	5.8	52	7.4	50.0	52	4.7	50.0
2003-Q3	71	3.9	33	4.7	46.5	38	3.5	53.5
2003-Q4	86	4.8	41	5.8	47.7	45	4.1	52.3
2004-Q1	73	4.0	31	4.4	42.5	42	3.8	57.5
2004-Q2	68	3.8	29	4.1	42.6	39	3.5	57.4
2004-Q3	65	3.6	37	5.3	56.9	28	2.5	43.1
2004-Q4	75	4.2	69	9.8	92.0	6	0.5	8.0
2005-Q1	51	2.8	50	7.1	98.0	1	0.1	2.0
2005-Q2	87	4.8	87	12.4	100.0	0	0.0	0.0
2005-Q3	63	3.5	63	9.0	100.0	0	0.0	0.0
2005-Q4	92	5.1	92	13.1	100.0	0	0.0	0.0
2006-Q1	20	1.1	20	2.8	100.0	0	0.0	0.0
Total	1,803	100.0	702	100.0	38.9	1,101	100.0	61.1

Table 2. Mean Characteristics of Downgrades by Dissemination

This table displays the mean event characteristics for the sample of bond rating downgrades by Moody's, S&P, and Fitch during July 1, 2001 to February 7, 2006. Variable definitions are provided in Panel A of Table A1. We split the sample into "Dissemination" and "No dissemination" groups based on whether or not TRACE publicly disseminated transactions in any of the issuer's downgraded bonds during the $(-31, -2)$ trading days before the date of downgrade. We compare the mean characteristics of "No dissemination" and "Dissemination" groups using two-tailed t-tests (assuming unequal variances). ***, **, and * denote that the mean differences reported in column 3 are significantly different from zero (two-tailed) at the 1%, 5%, and 10% level, respectively.

Characteristics	No dissemination (N=1,101)	Dissemination (N=702)	Difference in means	t-stat
Investment grade (%)	56.0	69.2	13.19***	(5.74)
Change in rating (no. of notches)	1.6	1.5	−0.08	(1.67)
LN(Days since last downgrade)	4.7	4.8	0.14	(1.45)
On negative watch (%)	56.0	76.1	20.03***	(9.11)
CDS reference entity (%)	55.9	85.8	29.90***	(14.98)
Contaminated announcement (%)	30.7	45.6	14.88***	(6.36)
Phase I (%)	1.1	0.6	−0.52	(1.23)
Phase II (%)	9.7	32.5	22.76***	(11.49)
Phase II (BBB-rated) (%)	3.9	11.7	7.78***	(5.77)
Phase IIIA (%)	41.5	41.0	−0.48	(0.20)
Phase IIIB (%)	33.7	6.1	−27.57***	(16.33)
Phase unknown (%)	10.1	8.1	−1.96	(1.43)

Table 3. Abnormal Stock Returns at Downgrade Announcements: Univariate Analysis

The sample consists of 1,803 corporate bond rating downgrades by the top three nationally recognized statistical rating organizations (Moody's, S&P, and Fitch) during July 1, 2001 to February 7, 2006. Table 1 provides details on the construction of the sample. We divide the sample into two groups, "Dissemination" and "No dissemination", based on whether or not the Trade Reporting and Compliance Engine (TRACE) publicly disseminated transactions in any of the issuer's downgraded bonds during the $(-31, -2)$ trading days before the date of downgrade (day 0). We define abnormal common stock return (CAR (in percentages)) as the actual ex post return minus the "normal" return of the stock, cumulated over the event window ($(-1, +1)$ trading day window centered on the date of rating downgrade). The "normal" return is the expected return of the stock without conditioning on the rating revision. We calculate it using Carhart's 4-factor model as the return-generating process. We obtain the parameters of the model using daily stock returns during the $(-252, -31)$ trading day estimation window. We require a minimum of 63 returns in the estimation window and 3 returns in the event window. To reduce the possible influence of outliers on our results, we eliminate observations in the top and bottom 1% of the sample based on CAR. Panel A presents the results for the full sample and Panel B presents the results for the subset of downgrades without confounding announcements (i.e., earnings announcements as well as 8-K, 10-Q, and 10-Q filings at any point time in the event window). To calculate the standardized cumulative abnormal return (SCAR), we scale CAR by the daily estimation window residual stock return volatility times the square root of three (number of trading days in the event window). ***, **, and * denote that the means or mean differences are significantly different from zero (two-tailed) at the 1%, 5%, and 10% level, respectively.

Panel A: Full Sample

	(1) All (N=1,803)			(2) Dissemination (N=702)			(3) No dissemination (N=1,101)			Difference in means (2) - (3)	
	Mean	S.E	Median	Mean	S.E	Median	Mean	S.E	Median	Mean	S.E
CAR	−2.59***	(0.23)	−0.69	−0.85***	(0.26)	−0.31	−3.71***	(0.33)	−1.15	2.86***	(0.46)
SCAR	−0.45***	(0.05)	−0.23	−0.22***	(0.08)	−0.15	−0.59***	(0.06)	−0.30	0.37***	(0.10)

Panel B: Non-contaminated Announcements

	(1) All (N=1,145)			(2) Dissemination (N=382)			(3) No dissemination (N=763)			Difference in means (2) - (3)	
	Mean	S.E	Median	Mean	S.E	Median	Mean	S.E	Median	Mean	S.E
CAR	−2.06***	(0.26)	−0.52	−0.30	(0.26)	−0.25	−2.94***	(0.36)	−0.77	2.64***	(0.54)
SCAR	−0.36***	(0.05)	−0.16	−0.10	(0.07)	−0.09	−0.48***	(0.07)	−0.20	0.38***	(0.11)

Table 4. Multivariate Analysis of Abnormal Stock Returns

This table presents ordinary least squares regressions of cumulative abnormal stock returns (in percentages) during the $(-1, +1)$ trading day window centered on the announcement date of rating downgrades. The sample consists of 1,803 corporate bond rating downgrades by the top three nationally recognized statistical rating organizations (Moody's, S&P, and Fitch) between July 1, 2001 and February 7, 2006. Table A1 provides the definitions of explanatory variables. Table 3 describes the calculation of abnormal stock returns. The omitted group in columns 3 and 4 is Phase I bonds. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

	Cumulative abnormal stock return (%)				
	(1)	(2)	(3)	(4)	(5)
Dissemination	2.86***	2.43***	1.94***	1.61**	3.29***
	(5.75)	(5.35)	(3.92)	(2.46)	(4.28)
Investment grade		1.23**	0.68	0.79	−3.44***
		(2.04)	(0.98)	(1.16)	(2.74)
Change in rating (no. of notches)		−0.74**	−0.70**	−0.69**	−0.37
		(2.26)	(2.14)	(2.02)	(0.96)
LN(Days since last downgrade)		0.44***	0.42***	0.37***	−0.00
		(3.42)	(3.33)	(3.00)	(0.02)
On negative watch		0.05	0.05	0.57	0.56
		(0.10)	(0.09)	(1.09)	(0.75)
CDS reference entity		1.31**	0.91	0.72	−0.41
		(2.13)	(1.60)	(1.26)	(0.36)
Contaminated announcement		−1.70***	−1.74***	−1.75***	−1.76***
		(3.20)	(3.31)	(3.37)	(3.00)
Phase II			0.26	−0.92	
			(0.17)	(0.52)	
Phase II (BBB-rated)			−0.65	−1.46	
			(0.40)	(0.80)	
Phase IIIA			−0.45	−0.71	
			(0.31)	(0.42)	
Phase IIIB			−2.42	−3.06*	
			(1.61)	(1.85)	
Phase unknown			−0.77	−1.79	
			(0.44)	(0.92)	
Constant	−3.71***	−5.52***	−3.83**	−3.13*	−0.61
	(9.36)	(5.07)	(2.39)	(1.81)	(5.84)
Year-Quarter FE	N	N	N	Y	Y
Industry FE	N	N	N	Y	N
Firm FE	N	N	N	N	Y
N	1803	1803	1803	1803	1803
R^2	0.021	0.061	0.068	0.101	0.342

Table 5. Robustness Checks
In this table, we examine the robustness of the regression results presented in Table 4. Specifications in columns 1 to 5 are identical to the respective specifications in Table 4. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively. For the definitions of contaminated observations and SCAR, see Table 3.

Panel A: Non-Contaminated Observations

	Cumulative abnormal stock return (%)				
	(1)	(2)	(3)	(4)	(5)
Dissemination	2.63***	1.75***	1.45***	1.45**	2.69***
	(5.38)	(3.82)	(2.98)	(2.03)	(2.87)
Constant	−2.94***	−3.90***	−0.84	−0.73	0.84
	(6.90)	(3.05)	(0.67)	(0.45)	(0.15)
Control variables	N	Y	Y	Y	Y
Phase FE	N	N	Y	Y	N
Year-Quarter FE	N	N	N	Y	Y
Industry FE	N	N	N	Y	N
Firm FE	N	N	N	N	Y
N	1145	1145	1145	1145	1145
R^2	0.020	0.065	0.075	0.107	0.407

Panel B: Dependent Variable is SCAR instead of CAR

	Cumulative abnormal stock return (%)				
	(1)	(2)	(3)	(4)	(5)
Dissemination	0.28***	0.26***	0.18**	0.33***	0.58***
	(3.24)	(2.89)	(1.98)	(2.73)	(4.11)
Constant	−0.49***	−0.67***	−0.53	−0.63***	0.09
	(8.28)	(3.62)	(1.50)	(2.58)	(0.09)
Control variables	N	Y	Y	Y	Y
Phase FE	N	N	Y	Y	N
Year-Quarter FE	N	N	N	Y	Y
Industry FE	N	N	N	Y	N
Firm FE	N	N	N	N	Y
N	1778	1778	1778	1778	1778
R^2	0.007	0.028	0.036	0.055	0.325

Table 6. Abnormal Bond Returns
This table presents ordinary least squares regressions of cumulative bond stock returns (in percentages) during the $(-1, +1)$ trading day window centered on the announcement date of rating downgrades by Moody's, S&P, and Fitch. Except for the dependent variable, the control variables and specifications are identical to the ones in Table 4. Our sample consists of 402 observations (141 downgrades where the issuer has no disseminated bonds and 261 downgrades where transactions of at least one of the downgraded bonds is publicly disseminated). Because data on bond returns is available only after July 2002, our sample period is one year shorter than the sample used in the abnormal stock return analysis (see Table 4). Moreover, we eliminate Phase I bonds, since we only have post-dissemination transaction information for them. To reduce the possible influence of outliers on our results, we eliminate observations in the top and bottom 1% of our sample based on abnormal bond returns. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

	Cumulative VW abnormal bond return (%)				
	(1)	(2)	(3)	(4)	(5)
Dissemination	3.32***	3.14***	2.35**	1.86*	1.92
	(3.44)	(3.36)	(2.61)	(1.92)	(1.32)
Constant	−4.44***	−5.58**	−3.26	−3.84**	−1.08
	(4.73)	(2.04)	(1.59)	(2.18)	(0.22)
Control variables	N	Y	Y	Y	Y
Phase FE	N	N	Y	Y	N
Year-Quarter FE	N	N	N	Y	Y
Industry FE	N	N	N	Y	N
Firm FE	N	N	N	N	Y
N	402	402	402	402	402
R^2	0.057	0.064	0.105	0.166	0.532

Table 7. Downgrades of Investor-Paid Egan Jones Ratings

We estimate the effect of dissemination on abnormal stock returns associated with downgrades of investor-paid Egan-Jones (EJR) ratings using ordinary least squares (OLS) regressions. The sample consists of 847 downgrades of issuer (i.e., firm-level) ratings by EJR between July 1, 2001 and February 7, 2006. To have a sample that is consistent with the samples in previous tables, we restrict the sample to issuers with at least one bond rating downgrade in Mergents Fixed Income Securities Database (FISD) during the sample period. The unit of observation is a firm rating event. Dissemination equals one if the firm has any outstanding bond whose transactions are disseminated via TRACE. Specifications in columns 1 to 5 are identical to respective specifications in Table 4. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

	Cumulative abnormal stock return (%)				
	(1)	(2)	(3)	(4)	(5)
Dissemination	3.16***	3.86***	3.31***	3.03**	4.89**
	(3.78)	(4.54)	(3.80)	(2.20)	(2.40)
Control variables	N	Y	Y	Y	Y
Phase FE	N	N	Y	Y	N
Year-Quarter FE	N	N	N	Y	Y
Industry FE	N	N	N	Y	N
Firm FE	N	N	N	N	Y
N	847	847	847	847	847
R^2	0.019	0.052	0.066	0.145	0.461

Table 8. Cross-Sectional Variation in the Effect of Dissemination

This table examines cross-sectional differences in the effect of TRACE dissemination on abnormal stock returns associated with announcements of bond rating downgrades. Table 1 provides details on sample construction. Panel A of Table A1 provides variable definitions. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

Information measures:	(1) Dissemination	(2) Information measure	(3) Dissemination × Information measure	(1) + (3)	N	R^2
(1) CDS reference entity	3.82***	1.79**	−2.13**	1.69**	1,803	0.095
	(3.58)	(2.37)	(2.11)	(2.56)		
(2) Exchange listed bonds	3.23***	1.69**	−1.89*	1.34*	1,803	0.092
	(3.88)	(2.01)	(1.91)	(1.72)		
(3) High stock liquidity	3.17***	1.15*	−1.88*	1.29*	1,803	0.092
	(3.39)	(1.81)	(1.96)	(1.86)		
(4) Low analyst forecast error	3.21***	2.99***	−2.67***	0.54	1,713	0.097
	(3.91)	(4.66)	(2.81)	(0.64)		
(5) Low analyst forecast dispersion	3.44***	2.45***	−3.17***	0.27	1,711	0.100
	(4.18)	(3.76)	(3.34)	(0.35)		
(6) Investment grade rating	4.85***	2.74***	−3.78***	1.07	1,803	0.097
	(4.88)	(3.15)	(3.47)	(1.56)		

Table 9. Flow of Information between Equity and Bond Markets

We examine the flow of information between bond and equity markets, before and after initiation of TRACE dissemination on the issuer's bonds, using 107,672 pairs of daily stock (with leads and lags) and value-weighted daily bond returns during July 2, 2002 and February 7, 2006 (447 unique firms and 908 unique trading days). We restrict the sample to domestic U.S. public issuers with at least one bond rating downgrade in Mergents Fixed Income Securities Database (FISD) during the sample period. Also, to be included in our analysis, an issuer must have available bond returns both before and after TRACE dissemination. Our base equation, presented in column 1, is based on Kwan (1996):

$$Ret^B_{i,t} = \beta_0 + \beta_1 Ret^E_{i,t+1} + \beta_2 Ret^E_{i,t} + \beta_3 Ret^E_{i,t-1} + \epsilon_{i,t}$$

Here, $Ret^B_{i,t}$ is the value-weighted bond portfolio return for firm i. The return on each bond issue equals the change in the daily trade-weighted yield, multiplied by -1. When calculating bond returns, we focus only on yields associated with institutional trades (trade size $\geq$ \$100,000). $Ret^E_{i,t}$ is the contemporaneous common stock return, $Ret^E_{i,t+1}$ and $Ret^E_{i,t-1}$ are the lead and lagged stock returns, and $\epsilon_{i,t}$ is the error term. All the returns are in percentages. To reduce the possible influence of large outliers on our results arising from data entry errors in TRACE, we eliminate observations that are in the top and bottom 1% of the daily bond returns distribution. In columns 2 to 4, we present models that include the interaction of stock returns with Dissemination dummy which equals 1 if transactions in at least one of the outstanding bonds of the issuer are publicly disseminated via TRACE on day t. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and double clustered at the firm and trading-day level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

	$Ret^B_{i,t}$			
	All	All	(-31, -2) trading days before a downgrade	No subsequent downgrade
	(1)	(2)	(3)	(4)
$Ret^E_{i,t+1}$	0.16***	0.08	0.02	0.09
	(2.96)	(1.21)	(0.18)	(1.26)
$Ret^E_{i,t}$	0.99***	0.88***	1.39***	0.71***
	(8.88)	(7.96)	(6.66)	(6.55)
$Ret^E_{i,t-1}$	0.86***	0.77***	1.12***	0.66***
	(10.80)	(9.28)	(6.44)	(7.90)
Dissemination $\times$ $Ret^E_{i,t+1}$		0.20**	0.57***	0.12
		(2.52)	(3.41)	(1.32)
Dissemination $\times$ $Ret^E_{i,t}$		0.25	0.43	0.29*
		(1.40)	(1.18)	(1.76)
Dissemination $\times$ $Ret^E_{i,t-1}$		0.20	0.32	0.23**
		(1.60)	(1.21)	(2.01)
Dissemination		-0.96***	-0.71	-0.97***
		(3.94)	(1.11)	(4.00)
Constant	1.11***	1.64***	1.53***	1.65***
	(6.48)	(6.73)	(2.80)	(6.76)
N	107672	107672	10710	96962
R^2	0.025	0.026	0.072	0.018

Table 10. The Sensitivity of Ratings to Market Prices After Dissemination

We estimate ordinary least squares regressions to examine the responsiveness of ratings to credit spread changes. Section 5 provides details on sample construction. Panel B of Table A1 provides variable definitions. Firm control variables include ln(assets), ln(sales), cash/assets, book leverage, return on assets, profit margin, and tangibility as well as the squared values of each of these variables. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and double clustered at the firm and year-month level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

	LN(Rating$_t$)		Pr(Downgrade$_t$=1)		Pr(Upgrade$_t$=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Spread$_t$	−6.19***	−0.70**				
	(14.40)	(2.31)				
Spread$_t$ × Dissemination$_t$	−3.27***	−1.10***				
	(3.80)	(3.17)				
ΔSpread$_t$			0.77*	0.76*	−0.03	−0.02
			(1.78)	(1.87)	(0.31)	(0.20)
ΔSpread$_{t-1}$			0.24	0.21	−0.13**	−0.13**
			(1.33)	(1.27)	(2.40)	(2.31)
ΔSpread$_t$ × Dissemination$_t$			0.85*	0.88*	−0.10	−0.18
			(1.87)	(1.89)	(0.66)	(1.05)
ΔSpread$_{t-1}$ × Dissemination$_{t-1}$			1.12***	1.21***	0.02	−0.06
			(2.58)	(2.75)	(0.17)	(0.46)
Dissemination$_t$	0.09***	0.03***	0.01*	0.01	−0.00	−0.00
	(3.70)	(4.47)	(1.96)	(1.45)	(0.29)	(0.63)
Dissemination$_{t-1}$			−0.01*	−0.01	0.00	−0.00
			(1.80)	(0.86)	(0.97)	(0.37)
Constant	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	N	N	N
Year-Month FE	N	Y	N	Y	N	Y
Firm control variables$_t$	N	Y	N	N	N	N
ΔFirm control variables$_t$	N	N	N	Y	N	Y
N	20954	19106	18299	16586	18299	16586
R^2	0.454	0.938	0.007	0.014	0.000	0.006

Table 11. The Predictive Power of Issuer Ratings for Future Default

We estimate the predictive ability of credit spreads (Panel A) and credit ratings (Panel B) for future default using linear probability models. Section 5 provides details on sample construction. Panel B of Table A1 provides variable definitions. Firm control variables include ln(assets), ln(sales), cash/assets, book leverage, return on assets, profit margin, and tangibility as well as the squared values of each of these variables. Absolute values of t-statistics based on standard errors that are heteroskedasticity-consistent and double clustered at the firm and year-month level are reported in parentheses beneath coefficient estimates. ***, **, or * denote that the coefficient estimate is significantly different from zero at the 1%, 5%, or 10% level, respectively.

Panel A. Predictive Power of Credit Spreads

	Pr(Default in the next two years)=1		
	(1)	(2)	(3)
Spread	0.92**	1.07**	1.27***
	(2.52)	(2.69)	(3.08)
Spread × Dissemination	1.41***	1.30***	1.28***
	(2.95)	(3.20)	(3.12)
Dissemination	−0.01	−0.01*	−0.03***
	(0.94)	(1.75)	(3.40)
Constant	Y	Y	Y
Year-Month FE	N	Y	Y
Industry (2-digit SIC Code) FE	N	Y	Y
Firm control variables	N	Y	Y
Phase FE	N	N	Y
N	20954	18859	18859
R^2	0.145	0.209	0.230

Panel B. Predictive Power of Credit Ratings

	Pr(Default in the next two years)=1		
	(1)	(2)	(3)
LN(Rating)	−0.060***	−0.040*	−0.072**
	(2.91)	(1.71)	(2.65)
LN(Rating) × Dissemination	−0.078**	−0.088**	−0.083**
	(2.25)	(2.60)	(2.54)
Dissemination	0.202**	0.233***	0.211**
	(2.26)	(2.71)	(2.55)
Constant	Y	Y	Y
Year-Month FE	N	Y	Y
Industry (2-digit SIC Code) FE	N	Y	Y
Firm control variables	N	Y	Y
Phase FE	N	N	Y
N	27167	24382	24382
R^2	0.076	0.179	0.196

Table 12. Predictive Accuracy of Credit Ratings versus Credit Spreads

We estimate the ability of credit ratings and credit spreads to predict default in the next two years using logit models with year-month fixed effects. We restrict the sample to firm-months with non-missing spread data. We estimate three sets of models: (i) models that include the natural logarithm of end-of-month S&P long-term issuer ratings, (ii) models that include the average monthly credit spreads, (iii) models that include both ratings and spreads. We report the results for the full sample, pre-dissemination sample, and post-dissemination sample. When the predicted default probability ≥ 0.5, we assume that the model predicts default. False positives are cases in which the model predicts default, but the issuer does not default. True positives are cases in which the model correctly predicts a future default event. The cumulative accuracy ratio is based on a non-parametric receiver operating characteristics (ROC) analysis examining how well ordinal rankings of firms by rating or credit spreads discriminates between firms that will and will not default.

	(1) Full sample (N=20,954)			(2) Pre-dissemination (N=7,602)			(3) Post-dissemination (N=13,352)		
	Rating	Spread	Both	Rating	Spread	Both	Rating	Spread	Both
Cumulative accuracy ratio (%)	90.15	93.48	93.73	85.17	92.48	92.32	93.36	94.87	95.31
False positive (%)	0.11	0.22	0.18	0.03	0.16	0.09	0.19	0.31	0.29
True positive (%)	9.09	20.55	19.37	2.56	12.82	10.26	15.43	26.86	29.14

Table A1. Variable Definitions

Panel A. Variables Used in Event Study Analysis

Variable Name	Data Source	Description
Dissemination	TRACE	Indicator variable that equals one if transactions in any of the issuer's downgraded bonds during the (-31,-2) trading days before the date of downgrade is publicly disseminated via TRACE.
Investment grade issuer	Compustat	Indicator variable that equals one if the S&P long-term issuer rating of the downgraded firm is BBB- or better at the end of the calendar month before the event month.
Change in rating	FISD	The size of downgrade in $\pm$ notches
Days since last downgrade	FISD	The number of calendar days since the most recent downgrade by a different rating agency. Following Jorion et al. (2005), we set this variable equal to 1,200 if no prior downgrade is observed or the number of days since the last downgrade is greater than 1,200.
On negative watch	FISD	Indicator variable that equals one if the downgraded bonds were put on negative watch by the rating agencies before the downgrade.
CDS reference entity	Bloomberg	Indicator variable that equals one if the issuer was a CDS reference entity at the time of the downgrade.
Contaminated announcement	Compustat, EDGAR	Indicator variable that equals one if the firm announced quarterly or annual earnings or filed a 10-K, 10-Q, or an 8-K report with the Securities and Exchange Commission (SEC) within (-1, +1) trading days centered on the date of rating downgrade. Earnings announcement dates are from the quarterly Compustat database (item code {RDQ}). The dates of 10-K, 10-Q, and 8-K filing are from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system.
Exchange listed bond	FISD, TRACE	Indicator variable that equals one if FISD indicates that the bond is anticipated to be listed on a domestic exchange after issuance or TRACE recorded a trade for the bond in more than 25 of the last 30 trading days.
High stock liquidity	CRSP	Indicator variable that equals one if the square root of the monthly illiquidity measure by Amihud (2002) multiplied by $1,000,000$ is less than the sample median (2.89%).
Low analyst forecast error	I/B/E/S	Indicator variable that equals one if the absolute distance between the median one-year analyst EPS forecast and the actual EPS, scaled by the stock price at beginning of the month in which forecasts were made, is less than the sample median (1.72%).
Low analyst forecast dispersion	I/B/E/S	Indicator variable that equals one if the standard deviation of analysts' one-year earnings per share (EPS) forecasts scaled by the beginning of month stock price is less than the sample median (0.36%).
Phase fixed effects	FINRA, TRACE	A set of variables that indicate the TRACE dissemination phase of the downgraded bonds. Phase II, IIIA, and IIIB indicators come directly from FINRA. If a bond is not in FINRA's list of Phase II, IIIA, and IIIB and if transactions on the bond were publicly disseminated before the implementation Phase II (according to the Enhanced TRACE database) we consider the bond a Phase I bond (just like Asquith et al. (2013)). We assign all remaining bonds to the "Phase unknown" group. If an issuer has bonds of different phases downgraded on the same date, we assign the earliest dissemination phase.

Panel B. Variables Used in Panel Data Analysis

Variable Name	Data Source	Description
LN(Rating)	Compustat	Natural logarithm of end-of-month S&P long-term issuer rating converted from alphanumerical to numeric scale; a lower numeric rating indicates a higher likelihood of default (CC (1), CCC- (2),..., AA+ (19), AAA (20)).
Credit spread	TRACE, FISD, FRED	We calculate firm-level monthly average credit spreads in six steps: (1) using an algorithm provided by Dick-Nielsen (2014), we eliminate canceled, corrected, reversed transactions from TRACE. We also eliminate double counted inter-dealer transactions, (2) we calculate the average daily yield of trades (weighted by trade size), separately for all outstanding fixed rate bonds of the issuer, using only yields associated with institutional trades (trade size $\geq$ \$100,000), (3) we calculate the daily yield spread of a bond by subtracting from the daily bond yield the yield associated with the Treasury security with the closest maturity, (4) we calculate the monthly yield spread of each bond as the simple average of the daily yield spreads, (5) we aggregate the monthly bond-level yield spreads to the issuer-level by calculating the average yield spread of all outstanding bonds of the issuer weighted by the remaining outstanding amount of each bond at the end of the month recorded by FISD, and (6) we set credit spreads to missing for firm-months at the top and bottom 1% of the credit spread distribution to reduce the possible influence of outliers on our results.
Default	Compustat, FISD	Indicator variable that equals one if in the next 24 months (1) the issuer's long-term S&P rating is downgraded to default (i.e., C, D, or SD), or (2) one or more of the issuer's bonds are downgraded to C or D by S&P, Moody's, or Fitch, according to FISD.
LN(Assets)	Compustat, FRED	Natural logarithm of book assets (ATQ) in \$millions, inflated to 2012 prices using the Consumer Price Index for All Urban Consumers.
LN(Sales)	Compustat, FRED	Natural logarithm of quarterly net sales (SALEQ) in \$millions, inflated to 2012 prices using the Consumer Price Index for All Urban Consumers.
Cash / Assets	Compustat	Cash / Book assets, CHEQ / ATQ.
Book leverage	Compustat	Total book debt / Book assets, [DLTTQ + DLCQ] / ATQ, constrained to lie between 0 and 1.
Return on assets	Compustat	EBITDA / Book assets, OIBDPQ / ATQ, winsorized at the bottom and top 1%.
Profit margin	Compustat	EBITDA / Sales, OIBDPQ / SALEQ, winsorized at the bottom and top 1%.
Tangibility	Compustat	Power, plant, and equipment (net) / Book Assets, PPENTQ / ATQ.