The Disciplining Effect of Short Sellers on Credit Rating Properties: Evidence from a Natural Experiment

Abstract: Using Regulation SHO as a controlled experiment, we examine the ex-ante disciplining effect of short sellers on credit rating properties. We find that rating informativeness improves, but rating stability declines for pilot firms relative to non-pilot firms when short sale constraints are removed for pilot firms. We also find less use of ratings in debt contracts for pilot firms relative to non-pilot firms when short sale constraints are removed for pilot firms. Our study should inform academics, practitioners, and regulators about short sellers' disciplining effect on credit rating properties, and provide novel evidence on rating agencies' tradeoff among different rating properties and its implication for rating usage.

Key Words: Short sellers; Credit rating properties; Credit rating agencies; Regulation SHO

JEL Classifications: G18; G23; G24

1. Introduction

Credit ratings help alleviate information asymmetry among the users and providers of capital and facilitate debt contracting and regulatory compliance (e.g., Beaver, Shakespeare, and Soliman 2006; Kisgen 2006). However, there are abundant rating inflation examples. The Justice Department filed a $5 billion lawsuit against Standard and Poor's (S&P) for granting AAA ratings to securities that the company knew were junk. S&P finally agreed to pay $1.5 billion to resolve the litigation (The Wall Street Journal 2015). It is therefore an important task to research and improve credit rating quality (e.g., Becker and Milourn 2011). After the prominent bankruptcy of the Enron, the Securities and Exchange Commission (SEC) certified more nationally recognized credit rating agencies hoping that competition can improve rating quality. The subsequent financial crisis reveal that competition alone is insufficient to incentivize high-quality ratings due to the breakdown of the reputational discipline; accordingly, serious rating inflation occurs for mortgage-backed securities before the 2008-2009 financial crisis (Mason and Rosner 2007). Lawmakers and regulators still contemplate further reforms to improve credit rating quality (U.S. House of Representatives 2011; Columbus Dispatch 2011). In this study, we explore a unique market force's (i.e., short sellers') disciplining effect on credit rating properties.

We are interested in short sellers' disciplining role for several reasons. First, short sellers are significant market forces – they represent 24% of NYSE and 31% of Nasdaq share volume (Diether, Lee, Werner 2009). Second, short sellers are specialized in providing downside risk information, which credit rating agencies, as debt market intermediaries, are highly concerned about. Since short sellers benefit directly from stock price declines, they have strong incentives to discover private negative information and trade overpriced securities, through which such negative information is incorporated into stock prices. Studies have demonstrated that short sellers reveal useful information, drive efficient prices, and lead to efficient resource allocations (Asquith, Pathak, and Ritter 2005; Chang, Cheng, and Yu 2007; Cohen, Diether and Malloy 2007). We are therefore interested in studying whether and how short sellers affect credit rating quality.

We predict that short sellers discipline rating agencies to issue more informative ratings, but at the cost of less stable ratings. Given the negative information revealed through short sales being relevant to credit-risk assessment, the prospect of short selling can increase rating agencies' reputational concerns by threatening to expose credit rating inaccuracies. As a result, rating agencies are less likely to intentionally inflate ratings and more likely to increase efforts and resources to issue more informative ratings. Meanwhile, short selling pressure can trigger rating agencies to take more frequent actions in response to new information about potential changes in credit risk before the additional confirmatory information becomes available, which can reduce rating stability.

To test our prediction, we use a controlled experiment, Regulation SHO (Reg SHO). The SEC adopted this program in July 2004, which mandated temporary suspension of short-sale price tests for a set of randomly selected pilot stocks during the period May 2, 2005, to August 6, 2007. Under Reg SHO, every third stock in the Russell 3000 index ranked by trading volume in each exchange (i.e., NYSE, NASDAQ, and AMEX) was selected as a pilot stock. Thus, the pilot program represents an exogenous shock to the constraints of short selling (e.g., Fang, Huang, and Karpoff 2016), resulting in a significant increase in short sales for stocks in the pilot program compared to those not in pilot program (e.g., SEC 2007; Alexander and Peterson 2008; Boehmer et al. 2008; Diether et al. 2009). Based on the Reg SHO setting, we adopt a difference-in-difference design to compare the differences of credit rating properties between pilot and non-pilot firms before and during the pilot program. Using the mapping between expected credit risk and credit rating to measure rating informativeness, we find that credit ratings become more responsive to expected credit risk for pilot firms than for non-pilot firms during the pilot program when short-sale price tests are removed. Since we control for the information contained in short sales, we interpret the evidence suggesting that short sellers ex-ante discipline rating agencies to issue more informative ratings.

To further corroborate the disciplining effect, we conduct several additional analyses. First, we run a few cross-sectional analyses and find that the disciplining effect of short sellers on credit rating informativeness is stronger when firms rely more on external financing, when firms have larger size, and when incumbent rating agencies (i.e., Moody's and S&P) face less competition from Fitch. Second, we restrict the analysis to a subsample without actual short sales (i.e, no direct information effect from short sellers); we continue to find that rating informativness improves. Third, we alternatively define the during period to start with the announcement date of Reg SHO and end on April 30, 2005, during which Reg SHO has not been implemented and hence actual short sales have not been affected. We find that rating informativeness improves for pilot firms during the window from the announcement of Reg SHO to April 30, 2005. Overall, these additional analyses further confirm short sellers' disciplining effect on rating informativeness.

We also run a series of sensitivity analyses to check robustness of our results on rating informativeness. Specifically, we examine other rating informativenss measures like the ability of ratings to predict future defaults and rating timeliness and find that these measures improve for pilot firms during the SHO period as well. We also control for the effect of earnings management, management forecasts, and analyst forecasts to address short sellers' potential indirect information effect and find that our results till hold. Taken together, various evidence supports the prediction that short sellers ex ante discipline rating agencies and improve credit rating informativeness.

Next, we examine the impact of short selling threat on rating stability and the corresponding implication for rating usage in debt contracts. We find that credit rating volatility increases for pilot firms relative to non-pilot firms during the pilot program when short sale threat increases. We follow deHann (2017) to examine rating usage in debt contracts using the relation between ratings and initial loan spread and the presence of rating-based performance pricing provision. Using both measures, we find less use of ratings in debt contracts for pilot firms relative to non-pilot firms when the threat of short sales increases. These findings suggest that although short sale pressure increases rating informativeness, it comes with a cost of increased rating volatility. As a result, debt contracting parties reduces their usage of ratings when short sale pressure increases.

Our paper makes several important contributions. First, this study contributes to the literature that examines determinants of and trade-offs among credit rating properties. Rating agencies often cite the trade-off between rating timeliness and rating stability as the justifications of not moving ratings in a timely manner (Standard & Poors 2006). Academic research also supports the view that high volatility in credit ratings is not desirable, since the use of credit ratings for contracting makes volatile ratings and unexpected rating reversals costly for the contracting parties (Beaver et al. 2006). However, relatively less attention has been paid to the tradeoff among different rating properties with the exception of Cheng and Neamtiu (2009), which show that investor criticism and regulatory pressure around the Sarbanes-Oxley Act (SOX) lead credit rating agencies to improve rating timeliness without sacrificing rating accuracy and rating stability. Our study extends the literature by documenting whether market force (i.e. prospect of short selling threat) affects rating properties and the tradeoff among different rating properties and by offering new evidence to recent academic call for research regarding to what extent market forces are sufficient for high rating quality (deHaan 2017). Moreover, by exploiting the exogenous variation generated by Reg SHO, this paper overcomes the difficulties to establish a causal link between ex-ante short selling threat and rating properties.

Second, this study has implications for regulators researching ways to increase credit rating properties and for market participants deciding when to rely on corporate ratings in debt contracting and pricing. Since credit rating agencies' failures around the 2008-2009 financial crisis, regulators have been exploring what went wrong in the crisis and various reforms to enhance rating quality (Manns 2013; deHaan 2017). Our findings could inform regulators about both the beneficial and especially damaging effects of short selling threat on credit rating properties. Our findings suggest that investors need to consider trade-offs between rating informativeness and rating stability. This study also warns rating users not to always rely more on ratings in debt contracting and pricing when rating agencies face increased reputation concerns.

Lastly, our paper adds to the recent literature studying the ex-ante disciplining role of short sellers. Massa et al. (2015) use international setting to find that short sellers discipline earnings management. Fang et al. (2016) use the Regulation SHO setting to further support the view that short seller can limit not only accruals-based earnings management but also corporate fraud. Recently, Chang et al. (2018) document that short sellers discourage managers from making value-destroying M&A. Extending and different from this line of research, our paper investigates the disciplining impact of short sellers on credit rating properties, which heavily affect debt instrument investing and debt contracting. Our results highlight an important new cost of short sellers to debt market participants – the increase of rating volatility and the decrease of rating usage. Thus, our findings imply that short sellers have different impacts on the debt market compared to the equity market and have implications for regulators debating costs and benefits of regulating short selling activities (SEC 2009).

Our paper is related to but distinct from Kecskes et al. (2013), which documents that short sellers provide valuable information to creditors in the bond market so that firms with high short interest are associated with lower credit ratings and higher yield spreads. First, the research questions are different. In Kecskes et al. (2013), short sellers are a source of risk-related information to creditors, while this study emphasizes the threat/prospect of short sellers on rating agencies' reputation concern. Given our research interest, we focus on credit rating informativness and stability and the trade-off between the two, while Kecsket et al. (2013) focus on credit rating levels. The results on rating levels do not have clear implications on rating properties (e.g., rating accuracy, rating timeliness, or rating volatility) (Narayanan 1985; Stein 1989; Verrecchia 1986; Bonsall 2014; deHaan 2017). Second, we further examine debt market participants' use of ratings. Our rating usage findings cannot be inferred from rating levels. Finally, we control for short interest in all empirical tests, indicating that the impact of short-selling threats on rating properties is beyond and above the information contained in short interest.

The rest of the paper is organized as follows. Section 2 provides background information and discusses related literature. Section 3 develops the prediction, describes the sample and the research design, and presents the empirical results for rating informativeness. Section 4 develops the prediction, describes the sample and the research design, and presents the empirical results for rating stability and usage. Section 5 concludes.

2. Background and Literature Review

2.1 Background

Since 1938, the SEC implemented the "price test" or "uptick rule" (Rule 10a-1) that allows short sales only when stock price has increased. The objectives of the rules as stated by the SEC are: "allowing relatively unrestricted short selling in an advancing market; preventing short selling at successively lower prices, thus eliminating short selling as a tool for driving the market down; and preventing short sellers from accelerating a declining market by exhausting all remaining bids at one price level, causing successively lower prices to be established by long sellers" (SEC 1963). Prior research studying the "uptick rule" generally finds that the uptick rule imposes binding constraints on short sales (Angel 1997; Alexander and Peterson 1999).

On July 28, 2004, the SEC announced the Regulation SHO program to formally study the effect of the uptick rule on financial markets. The program mandated temporary suspension of the uptick rule for a group of randomly selected stocks. Specifically, the SEC selected stocks from the Russell 3000 index listed on NYSE, NASDAQ, and AMEX and ranked them within each stock exchange by average daily trading volume. The SEC then picked every third stock on these lists as the pilot stocks, while the remaining stocks are non-pilot stocks. The pilot stocks were exempted from short-sale price tests during the period between May 2, 2005, and August 6, 2007. On July 6, 2007, the SEC removed short-sale price tests for all listed stocks including the non-pilot stocks. Given that the pilot stocks are picked randomly, the SEC experiment creates exogenous changes in short selling threat and provides an opportunity to study the causal effect of short selling threat.

2.2 Literature Review

2.2.1 Literature on the determinants of credit rating properties

The properties of credit ratings have gained increasing attention in the literature over time. Prior studies support the view that rating agencies' concern as honest and accurate rating providers contributes to high rating quality (e.g., Canter and Parker 1994; Covitz and Harrison, 2003; Smith and Walter 2002). For instance, Goel and Thakor (2011) analytically demonstrate that reputational concerns incentivize rating agencies to engage in costly information gathering. Empirically, Covitz and Harrison (2003) provide evidence that reputational concern dominates conflict of interest in influencing credit rating changes for Moody's and S&P. Xia (2014) finds that S&P's rating quality improves following the Egan-Jones Rating Company (EJR)'s coverage initiation because EJR's coverage elevated S&P's reputational concern. When the reputational concern is weakened by the increased competition from another issuer-pay rating agency Fitch, the incumbents (Moody's and S&P)' future rents decline. As a result, the incumbents are more likely to curry favor with issuers, which leads to lower rating quality (Becker and Milbourn 2011; Bar-Isaac and Shapiro 2010).[1]

The literature also documents that information is another key factor for rating agencies to maintain high rating quality because credit ratings are, to a large extent, based on information, both public and private information (S&P 2006; Moody's 2009). When public information is of low quality, the quality of credit ratings could suffer. In line with this view, Alissa, Bonsall, Koharki, and Penn (2013) find that earnings management helps firms with ratings deviating from the expected ratings move toward the expected ratings. Similarly, Zhang (2018) show that when firms with rating-based performance-priced debt contracts manage cash flow from operations and

[1] Many theoretical studies argue that the desire to have a positive reputation facilitates quality provision in markets where information issues may prevent it (e.g., Diamond 1989; Chemmnur and Fulghieri 1994).

accruals, their ratings are better. Access to private information could also influence credit rating quality. Jorion, Liu, and Shi (2005) find that the informational effects of upgrades and downgrades are much greater in the post Regulation Fair Disclosure period due to rating agencies' access to confidential information that is no longer available to the public. Bonsall, Koharki, and Neamtiu (2017) document that lack of access to private information through borrower's management at least partially contributes to EJR's lower rating accuracy, rating informativeness, and rating timeliness relative to S&P's when there is higher information uncertainty about borrowers.

The literature has paid relatively less attention to rating stability and the tradeoff of this rating property with other rating properties, although rating agencies themselves consider both important in the rating decision-making (Standard & Poor's 2006). deHann (2017) provides some evidence that rating stability improves after the financial crisis due to the public criticism and regulatory pressure. Cheng and Neamtiu (2009) document that rating agencies improve rating timeliness and accuracy and reduce rating volatility after the passage of SOX. Their evidence suggests that in response to increased regulatory pressure and investor criticism, credit rating agencies enhance rating timeliness without sacrificing rating accuracy and stability.

2.2.2 Literature on the effect of short selling

As arguably the most sophisticated players in the capital market (e.g., Hope et al. 2017), short sellers have a range of influence on targeted firms. Prior research finds that removing the uptick rule following Reg SHO results in increased short sales, wider spreads, thinner ask depth, and lower execution prices for pilot firms (Alexander and Peterson 2008, Diether et al. 2009, and the SEC 2007). Recently, Grullon et al. (2015) find that an increase in short selling leads to a decrease in equity issuance and investment for small firms. Massa, Zhang, and Zhang (2015) and Fang et al. (2016) find that short selling curbs earnings management, while Massa et al. (2015)

documents an increase in insider selling with the presence of short sellers. In addition, He and Tian (2016) find that short sellers improve corporate innovation as reflected in quality, value, and originality of patents, suggesting that short sellers mitigate managerial myopia.

A recent stream of literature also examines the impact of short sellers on market intermediaries. Cassell et al. (2011) document a positive association between short interests and audit fees. Similarly, Hope et al. (2017) find that auditors respond to the increased short selling threat by charging higher fees. Furthermore, Ke et al. (2018) find that after the removal of the price tests, financial analysts' earnings forecast quality increases for pilot firms. Overall, the literature suggests that short sellers influence not only the targeted firms, but also market intermediaries.

3. Credit rating informativeness

3.1 Prediction

Short sellers can discipline credit rating agencies to provide more informative ratings. Given the economic bond between issuers and rating agencies stemming from issuer-pay model, rating agencies have incentive to cater to clients, which will generate strategic biases in credit ratings (Kraft 2015). Since short sellers transmit negative information into stock prices, which is credit-risk relevant, they could increase rating agencies' reputational concerns by threatening to expose credit rating inaccuracies. As a result, in the presence of short selling threat, rating agencies are less likely to cater to their clients, which could reduce the strategic bias in ratings. The reputational concern could also push rating agencies to impose more efforts, use more resources, and hire more qualified personnel in the rating process, which could help reduce the unintentional bias in credit ratings. Supporting the above arguments, Piccolo and Shapiro (2017) analytically demonstrate that more informative trading leads to higher rating quality because such trading makes rating inflation more transparent and hence augments rating agencies' reputation costs.

As discussed above, Reg SHO program eliminated short-sale price tests for the pilot stocks; hence, it represents an exogenous shock to short sale activities and increases the prospect of short selling for pilot firms. Building on the disciplining mechanism, we predict that ratings become more informative for pilot firms relative to non-pilot firms during the reg-SHO program period.

However, we acknowledge that it is possible that short sellers may not discipline rating agencies to issue more informative ratings. Given the oligopoly structure of credit rating industry, reputational concerns may not be effective in curbing credit rating agencies to cater or in incentivizing them to exert more efforts and/or use more resources in the rating process. As a result, short selling threat will not be associated with rating informativeness. These arguments add tensions to our prediction.

3.2 Sample selection

We follow Diether, Lee, and Werner (2009) and Li and Zhang (2015) to compose our initial sample using the 2004 and 2005 versions of the Russell 3000 index. Specifically, we keep firms included in the Russell 3000 index during both 2004 and 2005. After combining this sample with the list of pilot stocks that the SEC announced on July 28, 2004, we obtain 876 unique pilot stocks and 1,757 unique non-pilot stocks. We next collect financial statement and short selling data from Compustat, stock market data from Center for Research in Securities Prices (CRSP), and default data, credit rating data, and issue-specific data from Fixed Investment Securities Database (FISD). To make balanced comparisons, our sample period includes two years before the implementation date of Reg SHO (May 2, 2005), between May 2000 and June 2002, and two years after this date, between May 2005 and June 2007.

In our analyses, we exclude firms in the financial service industry (SIC 6000-6999) because these firms are subject to further regulations and rating agencies have different considerations when rating these firms (S&P 2006). After deleting the observations with missing data on variables used in the main analyses, we obtain a final sample of 24,146 observations for 4,820 unique bond issues by 786 unique firms. The final sample includes 7,446 observations for 1,573 unique bond issues by 276 unique pilot firms and 16,700 observations for 3,247 unique bond issues by 510 unique non-pilot firms.

3.3 Research design

3.3.1 Key test variables

To identify the effect of short selling on credit rating informativeness through Reg SHO setting, we construct an indicator variable *PILOT* to distinguish between pilot firms (the treatment sample) and non-pilot firms (the control sample). *PILOT* takes the value of one if the stock is randomly selected by the SEC as a pilot stock and zero otherwise. We also follow Fang et al. (2016) to create a variable to indicate the period during the Reg SHO's pilot program: *DURING* equals one if a bond credit rating is assigned between May 2005 and June 2007 and zero if a bond rating is assigned between May 2000 and June 2002.

Our during-pilot period starts with May 2005 and ends in June 2007, since the pilot program effectively ran from May 2, 2005 to July 6, 2007. In defining the benchmark period, we follow the existing literature (e.g., Fang et al. 2016; Hope et al. 2017) to remove all observations in year 2004. The reason is that the SEC announced the list of the pilot firms on July 28, 2004 but did not remove the price tests for the pilot firms until May 2, 2005; hence, it is unclear whether credit rating agencies reacted in year 2004. We also exclude the latter half of year 2002 and the whole year 2003 because this period is the initial period after the passage of SOX, which contributes to higher rating accuracy and rating timeliness as shown by Cheng and Neamtiu (2009).

3.3.2 Empirical model

To examine the effect of short selling threat on credit rating informativeness, we follow prior research (e.g., Kedia et al. 2014; Xia 2014; Bonsall, Koharki, and Neamtiu 2015) to use the responsiveness of credit ratings to expected credit risk to evaluate rating informativeness. Specifically, we estimate the OLS regression model below:

$$\begin{aligned} RATING = {} & \alpha_0 + \beta_1 EDF \times PILOT \times DURING + \beta_2 EDF \times PILOT + \beta_3 EDF \times DURING \\ & + \beta_4 PILOT \times DURING + \beta_5 EDF + \beta_6 PILOT + \beta_7 DURING \\ & + \sum_{q=8}^{m} \beta_q (q^{th} Control\ Variables) + \sum Industry + \sum Year + \varepsilon \end{aligned} \tag{1}$$

In equation (1), *EDF* is the expected default probability derived from the Merton (1974)/KMV model; *RATING* is the numerical score of bond credit ratings issued by S&P's, Fitch, and Moody's. We follow Cheng and Neamtiu (2009) to convert letter ratings into numbers changing from 1 to 21, with 1 representing the best ratings and 21 representing the worst ratings (see Appendix A for details). In line with the literature, a higher correlation between *EDF* and *RATING* indicates that credit ratings are more responsive to expected credit risk and hence credit rating informativeness is higher, which corresponds to a positive and significant coefficient on *EDF*. The main variable of interest is the interaction term *EDF* × *PILOT* × *DURING*. If short selling threat improves credit rating informativeness for pilot firms relative to non-pilot firms, we expect the coefficient on this interaction term to be significantly positive.

Despite the use of a difference-in-difference design, we still include various control variables employed by prior research (Kedia et al. 2014; Xia 2014) to further separate the effect of short selling threat on credit rating informativeness from the effect of other variables. Specifically, we control for the following issuer characteristics: issuer size (*ISSUER_SIZE*), leverage (*LEV*), performance (*OPMARGIN*), and volatility (*RETSTD*). All accounting variables are measured at the fiscal year ending prior to the credit rating assignment dates. Similarly, issuer volatility is the standard deviation of daily stock returns over the fiscal year ending prior to the rating announcement dates. We include several issue characteristics: issue size (*ISSUE_SIZE*), the number of years until maturity (*MATURITY*), and an indicator variable for seniority status (*SENIOR*). We also control for two indicators for the rating agencies: *SP_RATING* and *FT_RATING*. Appendix B provides detailed variable definitions.

More important, we include short interest (*SHORT*) to control for the information contained in short interest. Short sellers' private information is incorporated into stock prices through their trading activities (Asquith et al. 2005; Chang et al. 2007; Cohen et al. 2007). Since rating agencies learn from the equity market (S&P 2006; S&P 2008; Piccolo and Shapiro 2017), they could incorporate the private information from short sellers into ratings, which could improve credit rating informativeness. To control for the effect of the information contained in short interest, we include short interests as an additional control variable in all our analyses.

Additionally, we include both industry and year fixed effects in all the regressions. To mitigate the concern for the potential within-issue correlations in the data, we report T-statistics using Huber-White standard errors corrected for issue clustering (Petersen 2009). To alleviate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

3.4 Descriptive statistics

Table 1 presents the descriptive statistics of the variables used in the baseline analysis. The mean (median) value of *RATING* is 9.830 (9.000), implying that the average (median) bond rating is close to BBB- or Baa3 (BBB or Baa2). This result suggests that rating agencies assign on average a credit rating toward the riskier side of the investment-grade spectrum. The average issuer size is $11 billion, while the average leverage is 0.306. The average standard deviation of daily stock return is 0.025, which is similar to that presented in Li and Zhang (2015). Firms in our sample are reasonably profitable with an average operating margin of 0.194, and smaller than those reported in Kedia et al. (2014). For issue characteristics, the average years to maturity is 7 years. About 84.5 percent of observations are senior issues. Overall, the statistics in our sample are comparable to those reported in prior research.

Table 2 presents the correlations for the variables used in the main analysis. Credit ratings and EDF are positively correlated, i.e., worse credit ratings correspond to higher EDF, suggesting that credit ratings are on average in line with the credit risk estimates implied by EDF. Worse credit ratings are also correlated with smaller issuer size, higher leverage, lower operating margin, higher volatility, smaller issue size, shorter maturity, less likely to be issued to senior issues, and more likely to attract short interest. These results are generally consistent with the findings in prior research.

3.5 Baseline results

Table 3 presents the results of estimating equation (1). Column 1 reports a positive and significant coefficient on EDF, suggesting that rating agencies assign worse credit ratings to issuers with higher expected credit risk than those with lower expected credit risk. The coefficient on *EDF* × *PILOT* × *DURING* is positive and significant at 1% level, indicating that the association between EDF and credit ratings becomes stronger for pilot firms than for non-pilot firms following the removal of the price tests. This result provides support for our prediction, suggesting that short selling threat improves credit rating informativeness.

In column 2, we include the control variables for issuer and issue characteristics, rating agency types, and short interest. The coefficient on *EDF* × *PILOT* × *DURING* continues to be positive and significant at 1% level, again supporting the prediction. The effect of short selling threat on credit rating informativeness is also economically significant. An increase of one standard deviation in EDF (0.201) is associated with a 0.34-notch downgrade in credit ratings for non-pilot firms following the removal of the price tests but with a 0.84-notch downgrade for pilot firms following the removal of the price tests.[2]

The coefficients on the control variables are also significant with the expected signs. For instance, the coefficients on *ISSUER_SIZE*, *OPMARGIN*, *MATURITY*, and *SENIOR* are all significantly negative, whereas the coefficients on *LEV*, *RETSTD*, and *ISSUE_SIZE* are all significantly positive. These results suggest that larger firm size, higher operating margin, longer maturity, and senior issue status are associated with better credit ratings, while higher leverage, higher volatility, and larger issue size correspond to less favorable credit ratings. The coefficient on *SHORT* is significantly positive, while the coefficient on *SHORT* × *EDF* is insignificant. Such empirical findings suggest that the information incorporated in short interest does not appear to have an impact on credit rating informativeness. Therefore, the informational mechanism may not be an important channel through which short sellers influence credit rating informativeness.

3.6 Robustness checks and additional analyses

3.6.1 Additional analyses of the disciplining mechanism

So far, we find robust causal evidence that short selling threat disciplines rating agencies to provide more informative ratings. In other words, given short sellers increase price informativeness (e.g., Hirshleifer, Toeh, and Yu 2011; Karpoff and Lou 2010), short selling increases the probability and speed with which the market participants and regulators uncover credit rating inaccuracies; hence, the prospect of short selling can either constrain rating agencies

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[2] In our main analyses, we primarily follow Kedia et al. (2014) to elect control variables and specify the model. As a robustness check, we further control for a few other issue characteristics used in the tests of another dimension of rating informativeness (i.e., rating timeliness), including *CONV*, *ENHANCE*, *PUT*, and *REDEEM*. The untabulated results are similar to those reported in Table 3 regarding the sign, magnitude, and significance for the coefficient on *EDF* × *PILOT* × *DURING*.

to cater to their clients or increase their resources and efforts in the rating process. To further corroborate this disciplining mechanism, we conduct three sets of additional analyses as discussed below.

Cross-sectional analyses

In this subsection, we examine the disciplining effect by exploring the cross-sectional variations of the influence of short selling threat on rating informativeness based on competition from Fitch, reliance on external financing, and firm size. We predict that the association between short selling threat and rating informativeness is weaker when the competition from Fitch is high, but stronger when reliance on external financing is high and firm size is large.

With the increased competition from Fitch, S&P's and Moody's could earn smaller future rents and hence become less concerned about their reputation and have weaker incentives to issue high-quality ratings (Becker and Milbourn 2011; Bar-Isaac and Shapiro 2010). Accordingly, S&P's and Moody's are less likely to react to the potential threat from short sellers when there is high competition from Fitch. When firms rely more on external financing, they are subject to more monitoring from various market participants (Bonsall et al. 2015), which increases rating agencies' reputational concern; hence, rating agencies are more likely to respond to short selling threat by reducing catering or increasing rating efforts in this case. Similarly, bigger firms attract more attention from market participants, e.g., more analyst following (Khan and Watts 2009); thus, rating agencies are more concerned about their reputational loss when rating larger firms and thereby reduce catering or increase their resources and efforts in the rating process in the presence of short selling threat.

Empirically, we follow Becker and Milbourn (2011) to capture competition from Fitch using Fitch market share (*FITCH_MS*) defined as the number of bond ratings issued by Fitch within an industry-year divided by the total number of bond ratings issued by all the three rating agencies in that industry-year. We measure reliance on external financing (*EXT_FINANCE*) as the sum of equity issuance and debt issuance. Specifically, similar to Leary and Roberts (2010), we define a debt issuance as a change in total book debt from period t-1 to t scaled by lagged total assets and an equity issuance as the difference between sale of common and preferred stock and purchase of common and preferred stock scaled by lagged total assets. We capture firm size (*FIRM_SIZE*) using the market capitalization.

We then calculate the average competition from Fitch, reliance on external financing, and firm size for each firm in the pre Reg SHO period, respectively. We next partition the sample of firms rated by S&P's and Moody's into two sub-samples, high versus low competition from Fitch, based on the sample median of the average *FITCH_MS* in the period before Reg SHO. Similarly, we partition the full sample into two sub-samples, high versus low reliance on external financing, using the sample median of the average *EXT_FINANCE* in the period before Reg SHO. We also partition the full sample into two sub-samples, large versus small firm size, using the sample median of the average *FIRM_SIZE* in the period before Reg SHO.

Panel A of Table 4 presents the results for the subsample analyses based on the above three partitioning variables. For brevity, we do not report the results on the control variables. The coefficients on *EDF* × *PILOT* × *DURING* are positive and significant for both the subsample with high Fitch market share and that with low Fitch market share, but the coefficient for the subsample with low Fitch market share is much bigger than that for the subsample with high Fitch market share (i.e., 38.981 vs. 3.459). The Wald-test statistic shows that the difference in the coefficients between the two subsamples is significant at 1% level. These results suggest that the incumbent rating agencies (i.e., S&P and Moody's) react less to short selling threat when the competition from Fitch is higher and accordingly the disciplining effect from short selling threat is weaker in this case.

Panel A of Table 4 also shows that the coefficient on the interaction term *EDF* × *PILOT* × *DURING* is positive and significant for the subsample with high reliance on external financing, but insignificant for the subsample with low reliance on external financing. The Wald-test statistic shows that the difference in the coefficients between the two subsamples is significant at 1% level. These results suggest that rating agencies respond more to short selling threat when firms rely more on external financing and hence the disciplining effect from short selling threat is stronger in this scenario.

Additionally, Panel A of Table 4 shows that the coefficients on *EDF* × *PILOT* × *DURING* are positive and significant for both the subsample with large firm size and that with small firm size, but the coefficient for the subsample with large firm size is much bigger than that for the subsample with small firm size (i.e., 29.187 vs. 3.375). The Wald-test statistic shows that the difference in the coefficients between the two subsamples is significant at 1% level. These results suggest that rating agencies are more responsive to short selling threat for larger firms and hence the disciplining effect from short selling threat is more pronounced for larger firms.

Analyses using the subsample without short sales

We further test the disciplining mechanism by analyzing the effect of short selling threat on rating informativeness using the subsample without actual short sales. In the subsample without actual short sales, it is unlikely that rating agencies learn new information from the market due to the improved price efficiency associated with short selling. Hence, this subsample provides us an opportunity to more cleanly identify whether short selling increases rating informativeness through the disciplining mechanism. Panel B of Table 4 reports the results of this analysis. It shows a significant and positive coefficient on *EDF* × *PILOT* × *DURING*, indicating that short selling threat increases rating informativeness, given that there are no actual short sales.

Analyses using an alternative way to define the during period

We also test the disciplining mechanism by alternatively defining the during period to be between the announcement date of Reg SHO and the implementation date of Reg SHO. Once the SEC announced the Reg SHO program, rating agencies could consider short selling threat present; but before the implementation of Reg SHO, actual short sales have not been influenced and hence the information contained in short sales is unlikely to be at play. Thus, this period in between the announcement of Reg SHO and the implementation of Reg SHO provides us an opportunity to identify short sellers' disciplining role in affecting rating agencies without being confounded by short sellers' informational role.

Specifically, we define an alternative during indicator, *DURING_b*, that equals one if a bond rating is assigned between August 2004 and April 2005 and zero if a bond rating is assigned between May 2000 and June 2002. We then replace *DURING* with *DURING_b* and re-estimate equation (1). Panel C of Table 4 presents the results. Column (1) includes all the control variables from equation (1) except the controls for the effect of short sales, since short sales have not been influenced in this alternative during period. It shows a significantly positive coefficient on *EDF* × *PILOT* × *DURING_b*, suggesting that ratings are more responsive to expected credit risk for pilot firms than for non-pilot firms after the announcement of Reg SHO but before the implementation of Reg SHO. As a robustness check, we include *SHORT* and its interaction with *EDF* into the model in column (1) and then re-estimate the regression. As shown in column (2), the coefficient on *EDF* × *PILOT* × *DURING_b* continues to be positive and significant, again confirming that rating informativeness gets higher for pilot firms than for non-pilot firms after the announcement of Reg SHO but before the implementation of Reg SHO.

Overall, Table 4 provides evidence that the influence of short selling threat on rating informativeness is weaker when the competition from Fitch is higher, but stronger when reliance on external financing is higher and firm size is larger. This evidence suggests that due to the heightened reputational concern, rating agencies respond to short selling threat by either reducing catering or increasing rating resources and efforts when competition from Fitch is lower, reliance on external financing is higher, and firm size is larger, thereby increasing rating informativeness. Table 4 also shows that the influence of short selling threat on rating informativeness is present when we use the subsample without actual short sales and define the during period as between the announcement of Reg SHO and its implementation. Taken together, Table 4 provides additional support that short sellers discipline rating agencies to improve rating informativeness.

3.6.2 Additional controls for the effect of information environment

Although we recognize and address short sellers' direct informational effect by controlling for short sales throughout the analyses, one may argue that short sellers' indirect informational effect can still drive our results. In other words, short selling prospect can constrain earnings management, increase and improve management forecasts, and enhance analyst forecast quality, which may in turn lead to higher rating informativeness, given that rating agencies could incorporate financial reporting, management forecasts, and analyst forecasts in their rating decisions. Recent studies indeed show that short selling prospect constrains earnings management (Massa et al. 2015; Fang et al. 2016) and the ease of short selling improves analyst earnings forecast quality (Ke et al. 2018). However, studies provide mixed evidence on the implication of short selling threat on management forecast – Li and Zhang (2015) show that short selling pressure reduces the precision of bad news forecasts, while Chen et al. (2019) indicate that short selling threat induces managers to issue more long-run good news forecasts. To address short sellers' potential indirect information effect, we include additional controls for the effect of earnings management, management forecasts, and analyst forecasts.

Specifically, we follow prior studies (e.g., Jones 1991, Dechow, Sloan and Sweeney 1995) to capture earnings management using abnormal accruals (*ABACC*) and restatement (*RESTATE*). We follow Dhaliwal, Khurana, and Pereira (2011) to identify the effect of management forecast using the precision of management forecast (*PRECISION*) and disclosure policy (*DISCLOSURE*). We follow prior studies (O'Brien and Bushman 1990; Bowen, Chen and Cheng 2004), to identify the effect of analyst forecast by using analyst following (*NANAL*) and analyst forecast accuracy (*AF_ACCURACY*). Appendix B provides details on the definitions of these variables. We then augment equation (1) with one of the above additional controls at a time and its interaction with *EDF*.

Table 5 presents the results of the analyses. In column (1), we include earnings management as captured by abnormal accruals (*ABACC)* and its interaction with *EDF*. We find a positive and significant coefficient on *EDF* × *PILOT* × *DURING*. In column (2), we repeat the test in column (1) by replacing abnormal accruals with an alternative measure of earnings management, *RESTATE*, and find similar results. In columns (3) and (4), we include the effect of management forecast by adding *PRECISION* and *DISCLOSURE*, respectively, and its corresponding interaction with *EDF*. We continue to find significantly positive coefficients on *EDF* × *PILOT* × *DURING*. In columns (5) and (6), we include the effect of analyst forecast by adding *NANAL* and *AF_ACCURACY*, respectively, and its corresponding interaction with *EDF*.

We find that our results still hold. Therefore, it is unlikely that the impact of short selling threat on rating informativeness we document is driven by short sellers' indirect information effect.

3.6.3 Alternative measures of credit rating informativeness

The ability of credit ratings to predict future defaults

In this subsection, we examine the robustness of our results to alternative measures of credit rating informativeness. Following Becker and Milbourn (2011) and Badoer and Demiroglu (2019), among others, we alternatively capture rating informativeness using the ability of ratings to predict future default. Specifically, we relate current credit ratings to future default events by estimating the following logit model:

$$\begin{aligned} DEFAULT\_3YR = {} & \alpha_0 + \beta_1 RATING \times PILOT \times DURING + \beta_2 RATING \times PILOT \\ & + \beta_3 RATING \times DURING + \beta_4 PILOT \times DURING + \beta_5 RATING \\ & + \beta_6 PILOT + \beta_7 DURING + \sum_{q=8}^{m} \beta_q \, (q^{th} Control \quad Variables) \\ & + \sum Industry + \sum Year + \varepsilon \qquad (2) \end{aligned}$$

where *DEFAULT_3YR* is an indicator variable that takes one if there is a default in three years from the rating date, and zero otherwise; other variables are defined as above. The higher correlation between *RATING* and *DEFAULT* indicates the higher ability of ratings to predict future defaults and hence higher rating informativeness. If short selling threat improves the ability of ratings to predict future default events, the coefficient on *RATING* × *PILOT* × *DURING* is expected to be significantly positive.

Panel A of Table 6 reports the results of estimating equation (2). Column (1) shows a significantly positive coefficient on *RATING*, suggesting that issues with worse ratings are more likely to default in the future. The coefficient on *RATING* × *PILOT* × *DURING* is positive and significant, suggesting that the ability of ratings to predict future defaults becomes stronger for pilot firms than for non-pilot firms following the removal of the price tests. In column (2), we include the control variables for issuer and issue characteristics, rating agency types, short sales, as well as additional control variables from Badoer and Demiroglu (2019) (*SALE*, *CASH*, *ROA*, and *CAP_INTEN*). We continue to find a positive and significant coefficient on *RATING* × *PILOT* × *DURING*. In summary, panel A of Table 6 suggests that short selling threat increases the ability of ratings to predict future defaults, providing further support for our prediction.

Credit rating timeliness

We also conduct robustness checks by examining the impact of short selling threat on credit rating timeliness. Specifically, we follow Cheng and Neamtiu (2009) and deHaan (2017) to construct two alternative proxies for rating timeliness, *DAYAHEAD* and *WRATE*. *DAYAHEAD* is the natural log of the number of days between the default date and the last speculative-grade rating assigned on or before the default date. *WRATE* is the weighted average rating level during the one year leading to default. We then estimate the following model using OLS regression:

$$\begin{aligned} TIMELINESS = {} & \alpha_0 + \beta_1 PILOT \times DURING + \beta_2 PILOT + \beta_3 DURING \\ & + \sum_{q=4}^{m} \beta_q (q^{th} Control\ Variables) + \sum Industry + \sum Year + \varepsilon \end{aligned} \tag{3}$$

where *TIMELINESS* is either *DAYAHEAD* or *WRATE*.

Panel B of Table 6 presents the results. Column (1) shows a positive and significant coefficient on *PILOT* × *DURING*, suggesting that credit ratings become timelier for pilot firms than for non-pilot firms following the removal of the price tests. In column (2), we include the controls for issuer and issue features, rating agency types, short sales, as well as additional issue features from Cheng and Neamtiu (2009) (*CONV*, *ENHANCE*, *PUT*, and *REDEEM*). We continue to find a significantly positive coefficient on *PILOT* × *DURING*. Columns (3) through (4) repeat the analyses in the first two columns using *WRATE* as the dependent variable and find similar results. Taken together, Panel B of Table 6 indicates that short selling threat increases credit rating timeliness, again supporting the prediction.

3.6.4 Untabulated robustness checks

We conduct a number of tests to check whether our results are robust to the following: (i) alternative definitions of the pre-SHO period; (ii) restricting the sample to issuing firms that are present both before and during the pilot program; (iii) addressing potential bias from correlations among bonds of the same issuer; and (iv) additional controls of the interactions between *DURING* and explanatory variables.

Alternative definitions of the pre-SHO period

We use two alternative definitions of the pre-SHO period. First, we exactly follow Fang et al. (2016) to define the pre-SHO period as the period between May 2001 and June 2003. Second, similar to the robust check of prior studies (Fang et al. 2016; Hope et al. 2017), we include 2004 and define the pre-SHO period as the period between May 2002 and June 2004. The untabulated results are similar to those reported in Table 3, providing further support that short selling threat is associated with higher credit rating informativeness.

Restricting the sample to the same set of firms

More short sales following the pilot program may lead some firms to go out of business, which could change the composition of sample firms. To alleviate the concern that that this change contaminates our results, we limit the sample to the same set of firms in periods both before and after the pilot program and re-estimate equation (1). The unbabulated results still show a positive and significant coefficient on *EDF* × *PILOT* × *DURING* at 1% level.

Potential biases from correlations among bonds issued by the same issuer

In our sample, one firm could issue several bonds and one bond can be rated by three rating agencies. Since ratings for bonds issued by the same firm tend to be correlated due to common firm characteristics, these correlations could lead to upward bias in t statistics in our analyses. To address this concern, we have clustered the standard errors at the issue level and controlled for two indicators for rating agencies, *SP_RATING* and *FT_RATING*, throughout the paper. To further alleviate this concern, we follow Kedia et al. (2014) to conduct two additional analyses. First, we re-estimate equation (1) after including firm fixed effects. We still find that the coefficient on *EDF* × *PILOT* × *DURING* is similar to those reported in Table 3 in sign, significance, and magnitude.

Second, we re-estimate equation (1) using only one bond per firm. That is, we keep firms that have bonds both in the pre-SHO and during-SHO periods and select their largest issues during each period. Using this subsample to re-estimate equation (1), we continue to find a positive and significant coefficient on *EDF* × *PILOT* × *DURING*. Taken together, these analyses confirm that our results are unlikely to be driven by the bias arising from potential correlations among bonds issued by the same firms.

Additional controls of the interactions between *DURING* and explanatory variables

To address the potential concern that issuer and issue features may change from the pre period to the during period, we, similar to Hope et al. (2017), interact all the control variables with *DURING* and continue to find the coefficient on *EDF* × *PILOT* × *DURING* to be similar to those in Table 3 regarding the sign, significance, and magnitude. Thus, our findings are robust to additional controls of the interactions between *DURING* and explanatory variables.

3.6.5 The permanent remove of the price tests

On July 6, 2007, the SEC removed the short-sale price tests for all firms, which should reduce short-sale constraints for non-pilot firms to a similar level just as for pilot firms after July

6, 2007. This setting provides us another exogenous shock to short selling threat but for non-pilot firms; hence, we take advantage of it to examine whether short selling threat similarly increases credit rating informativeness for non-pilot firms after the removal of price tests. We also investigate whether there is any significant difference between pilot firms and non-pilot firms in terms of rating informativeness after the price tests are eliminated for both groups of firms.

Specifically, we re-estimate equation (1) after replacing variable *DURING* with *POST*, which is an indicator that takes one if ratings are issued between August 2007 and September 2010 and zero if ratings are issued between May 2000 and June 2002. Table 7 presents the results. The coefficient on *EDF* × *POST* is positive and significant, suggesting that rating agencies respond to short selling prospect after the removal of the price tests for non-pilot firms by either reducing catering or increasing rating resources and efforts, which leads to higher rating informativeness for non-pilot firms in the post period. The coefficient on *EDF* × *PILOT* × *POST* is insignificant, suggesting that there is no significant difference between pilot firms and non-pilot firms regarding rating informativeness after the elimination of the price tests for both groups of firms. Overall, Table 7 provides additional evidence supporting our prediction that short selling prospect contributes to higher rating informativeness.

4. Credit rating stability and credit rating usage

4.1 Credit rating stability

4.1.1 Prediction

We also examine the impact of short selling threat on rating stability, since rating stability is an important rating property considered in debt contracting (Beaver et al. 2006). Although short selling threat pushes rating agencies to improve rating informativeness, this improvement could come at the cost of lower rating stability. With the presence of short selling threat, rating agencies could take timelier actions in response to new pieces of information about potential changes in issuers' credit risk, even though the long-term implications of such new information can only be fully understood over time. When rating agencies no longer wait for the additional confirmatory information to become available, ratings are more likely to reverse in the future, which in turn increases rating volatility. We therefore predict that ratings will be less stable for pilot firms relative to non-pilot firms during the reg-SHO period.

On the other hand, improved rating informativeness for pilot firms during the reg-SHO period does not necessarily come at the expense of lower rating stability. If rating agencies are able to improve credit analysis and at the same time push the rating informativeness-stability frontier (i.e., rating agencies may gather additional information to ensure the timer rating actions are warranted and hence not reserved later), we may not observe any change in rating stability as short selling threat increases for pilot firms during the reg-SHO program.

4.1.2 Research design

To examine the effect of short selling threat on credit rating stability, we follow prior research (e.g., Cheng and Neamtiu 2009; deHaan 2017) to capture rating stability using the standard deviation of ratings outstanding over the yearly rolling window from May 1st of each year through April 30th of the next year (*VOLATILITY*). We choose May 1st as our yearly cutoff point because May 1, 2005 is the date that separates our pre and during period. In calculating *VOLATILITY*, we require at least three ratings during the year. Then we estimate the following model using OLS procedure:[3]

$$VOLATILITY = \alpha_0 + \beta_1 PILOT \times DURING + \beta_2 PILOT + \beta_3 DURING$$

[3] The sample selection for rating stability tests is same as that for rating informativeness.

$$+ \sum_{q=4}^{m} \beta_q \,(q^{th} Control \quad Variables) + \sum Industry + \sum Year + \varepsilon \qquad (4)$$

In the above equation, we follow Cheng and Neamtiu (2009) and deHaan (2017) to include a set of issuer (*ISSUER_SIZE*, *COV*, *LEV*, *NEG_RET*) and issue features (*ISSUE_SIZE*, *MATURITY*, *SENIOR*, *CONV*, *ENHANCE*, *PUT*, and *REDEEM*), rating agency types (*SP_RATING* and *FT_RATING*), short sales (*SHORT*), and ratings right before the yearly window (*RATELAG*) as control variables. Appendix B provides detailed definitions for all the variables. We also include industry and year fixed effects in all the regressions. Given our prediction that short selling threat leads rating agencies to issue less stable (i.e., more volatile) ratings, we expect the coefficient on *PILOT* × *DURING* to be positive.

4.1.3 Empirical results

Table 8 presents the results of estimating equation (4). In column (1), we do not include any control variables. It shows a positive and significant coefficient on *PILOT* × *DURING*, suggesting that credit ratings become more volatile for pilot firms than for non-pilot firms following the removal of the price tests. In column (2), we include the controls for issuer and issue features, rating agency types, short sales, and ratings right before the yearly window and continue to find a significantly positive coefficient on *PILOT* × *DURING*. In short, Table 8 indicates that short selling threat reduces credit rating stability, consistent with our prediction.

4.2 Credit rating usage

4.2.1 Prediction

Given the evidence on the relation between short selling threat and rating properties, we next examine whether short selling threat influences the use of credit ratings in debt contracts. On the one hand, when ratings become more informative in the presence of short selling threat, debt contracting parties could increase their reliance on ratings due to the additional information content in ratings. On the other hand, debt contracting parties may use ratings to a lesser extent since ratings become more volatile in the presence of short selling threat. Ratings are often used for long-term purposes in debt contracts, for instance, as rating triggers or in rating-based performance price provisions. As a result, more volatile ratings are less suitable to be used in debt contracts either as rating triggers or as benchmarks in rating-based performance pricing provisions. Thus, it is ex-ante not clear which force dominates. For this reason, we empirically examine the change of the rating usage in the presence of short selling threat stemming from the Reg SHO program.

4.2.2 Sample selection

We obtain loan data from DealScan, which provides a variety of information about loan contracts, including loan spread and performance pricing features. We merge DealScan dataset with the DealScan-gvkey linking table from Chava and Roberts (2008) that is updated through April 2018. Then we merge this dataset with the dataset that we use to test the mapping between *EDF* and credit rating in Section 3. Since loan-specific ratings are usually not available, we follow deHaan (2017) to match each loan to the most recent bond issue ratings, but we require that loan start date not be 5 years away from rating date. We also exclude firms in the financial service industry (SIC 6000-6999) and require non-missing loan data for variables used in the analyses of the relation between rating and loan spread. This selection procedure leads to the final sample for the tests of the rating-loan spread relation, which consists of 30,453 observations representing 662 firms and 3,651 loans.

For the tests of rating-based performance pricing provisions, we further require non-missing data for performance pricing provisions. Keeping only loans with at least one performance pricing provision allows us not to assume that loans do not have a performance pricing provision when they are missing from DealScan's "Performance Pricing" file. The final sample for the tests of rating-based performance pricing provision includes 17,071observations representing 596 firms and 2,206 loans.

4.2.3 Research design

To examine the effect of short selling threat on debt contracting usage of credit ratings, we follow deHaan (2017) to use the relation between credit rating and loan spread and the presence of rating-based performance pricing provisions to assess debt contracting usage of credit ratings. For the rating-loan spread relation, we estimate the following model using OLS procedure:

$$\begin{aligned} SPREAD = {} & \alpha_0 + \beta_1 RATING \times PILOT \times DURING + \beta_2 RATING \times PILOT \\ & + \beta_3 RATING \times DURING + \beta_4 PILOT \times DURING + \beta_5 RATING \\ & + \beta_6 PILOT + \beta_7 DURING + \sum_{q=8}^{m} \beta_q \left(q^{th} Control \quad Variables \right) \\ & + \sum Industry + \sum Year + \varepsilon \end{aligned} \tag{5}$$

where *SPREAD* is the logged interest spread at the debt issuance; *RATING*, *PILOT*, and *DURING* are defined as before. In line with deHaan (2017), a higher correlation between *RATING* and *SPREAD* indicates that credit ratings are more relevant to loan spread, which corresponds to a positive and significant coefficient on *RATING*. The main variable of interest is the interaction term *RATING* × *PILOT* × *DURING*. If short selling threat reduces (increases) the relevance of ratings to loan spread, we expect the coefficient on this interaction term to be significantly negative (positive).

Regarding the rating-based performance pricing provisions, we estimate the following model using OLS procedure:

$$\begin{aligned} PP\_RATING = {} & \alpha_0 + \beta_1 PILOT \times DURING + \beta_2 PILOT + \beta_3 DURING \\ & + \textstyle\sum_{q=4}^{m} \beta_q \left(q^{th} Control \quad Variables \right) + \sum Industry + \sum Year + \varepsilon \end{aligned} \tag{6}$$

where *PP_RATING* is an indicator variable that takes one if the loan has a rating-based performance pricing provision and zero otherwise; *PILOT* and *DURING* are defined as before. The main variable of interest is the interaction term *PILOT* × *DURING*. If short selling threat reduces (increases) the usage of rating-based performance pricing provisions, we expect the coefficient on this interaction term to be significantly negative (positive).

In spite of the difference-in-difference design, in both equations (5) and (6) we still include a set of issuer and issue features, rating agency types, shore interest, as well as loan features as control variables to further distinguish the effect of short selling threat on rating usage from the effect of other variables. In particular, issuer features include issuer size (*ISSUER_SIZE*), leverage (*LEV*), and performance (*ROA_b*). Issue features include issue size (*ISSUE_SIZE*), issue maturity (*MATURITY*), and seniority status (*SENIOR*). Loan features include the amount (*LOAN_SIZE*), the maturity (*LOAN_MATURITY*), number of lenders (*LENDERS*), indicator of being a revolving loan (*REVOLVER*), status of being an institutional loan (*INST_INVST*), whether the loan is backed up by collateral (*SECURED*), and whether the lead arranger has recent experience with the borrower (*RELATION*). For the tests of rating-based performance pricing, the control variables also include credit rating level (*RATING*). Appendix B provides more details on the definitions of all the variables. We also include industry and year fixed effects in all the regressions. To mitigate the concern for the potential within-issue correlations in the data, we report t-statistics using Huber-White standard errors corrected for issue clustering (Petersen 2009). To alleviate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

4.2.4 Empirical results

Panel A of Table 9 presents the results of estimating equation (5). In column (1), we do not include control variables. It shows a positive and significant coefficient on *RATING*, suggesting that worse ratings are associated with higher loan spread. The coefficient on *RATING* × *PILOT* × *DURING* is negative and significant at 1% level, indicating that the relation between rating and initial loan contract spread becomes weaker for pilot firms than for non-pilot firms following the removal of the price tests. This result provides support for our prediction, suggesting that short selling threat reduces the relevance of credit rating to loan spread. In column (2), we include the control variables for issuer and issue features, rating agency types, short interest, and loan characteristics. The coefficient on *RATING* × *PILOT* × *DURING* continues to be negative and significant at 1% level, again supporting the prediction.

Panel B of Table 9 presents the results of estimating equation (6). Column (1) shows a significant and negative coefficient on *PILOT* × *DURING*, suggesting that rating-based performance pricing provisions are less likely to be used in debt contracts for pilot firms than for non-pilot firms following the removal of the price tests. In column (2), we include the control variables for issuer and issue features, rating agency types, short sales, loan features, as well as credit rating. We continue to find a significant and negative coefficient on *PILOT* × *DURING*.[4] Put together, table 9 provides consistent evidence that short selling threat reduces the usage of credit rating in debt contracts for pilot firms relative to non-pilot firms. These findings are consistent with the increased rating volatility results rather than the increased rating informativeness results, suggesting that debt contract users trade off these two important rating properties.

5. Discussions and Conclusions

[4] As a robustness check, we re-estimate equation (6) using logit procedure. The untabulated results are qualitatively similar to those reported in the paper.

Short sellers are a group of sophisticated market participants, who have incentives to collect and trade on firms' downside information. As a result, short sellers can increase rating agencies' reputational concern by threatening to expose credit rating inaccuracies. Therefore, we examine short sellers' disciplining role on credit rating properties.

Empirically, we test whether and how short sellers affect credit rating properties using Regulation SHO as a controlled experiment. Under Reg SHO, every third stock in the Russell 3000 index ranked by trading volume in each exchange was selected as a pilot stock. As a result, pilot firms experience an exogenous increase in short sale threat compared to non-pilot firms during the SHO period. Exploiting this exogenous variation in short sale threat, we adopt a difference-in-difference design to compare credit rating properties between pilot and non-pilot firms before and during the pilot program. We find higher rating informativness for pilot firms than for non-pilot firms during the pilot program as reflected in credit ratings' better mapping with underlying default risks, higher ability to predict future defaults, and increased timeliness.

To further corroborate the disciplining effect, we conduct several additional analyses. First, we run a few cross-sectional analyses and find that the disciplining effect of short sellers on credit rating informativeness is stronger when firms rely more on external financing, when firms have larger size, and when incumbent rating agencies (i.e., Moody's and S&P) face less competition from Fitch. Second, we restrict the analysis to a subsample without actual short sales (i.e, no direct information effect from short sellers); we continue to find that rating informativness improves. Third, we alternatively define the during period to start with the announcement date of Reg SHO and end on April 30, 2005, during which Reg SHO has not been implemented and hence actual short sales have not been affected. We find that rating informativeness improves for pilot firms during the window from the announcement of Reg SHO to April 30, 2005. Overall, these additional analyses further confirm short sellers' disciplining effect on rating informativeness.

We also examine the impact of short selling threat on rating stability and the corresponding implication for rating usage in debt contracts. We find that compared to non-pilot firms, pilot firms experience more volatile ratings in the post Reg SHO period. This finding is consistent with the trade-off between rating informativeness and rating stability as discussed by rating agencies (Standard and Poors 2006). We also document less rating usage in debt contracts for pilot firms than for non-pilot firms during the Reg SHO period.

Overall, different from prior studies who mainly focus on the beneficial effects of short sellers (Kecskes et al. 2013; Fang et al. 2016; Massa et al. 2015; Hope et al. 2017), our study highlights the trade-off between rating informativeness and rating volatility. The findings are not only informative to academic researchers but also useful for regulators who remain interested in improving credit rating quality. Our findings should also warn market participants not to simply rely more on corporate ratings in debt contracting and pricing when rating agencies' reputation concern is high.

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Appendix A: Rating schemes definitions

Credit risk	Moody's	S&P's	Fitch's	Code assigned
Highest grade	Aaa	AAA	AAA	1
	Aa1	AA+	AA+	2
High grade	Aa2	AA	AA	3
	Aa3	AA-	AA-	4
	A1	A+	A+	5
Upper medium grade	A2	A	A	6
	A3	A-	A-	7
	Baa1	BBB+	BBB+	8
Medium grade	Baa2	BBB	BBB	9
	Baa3	BBB-	BBB-	10
	Ba1	BB+	BB+	11
Lower medium grade	Ba2	BB	BB	12
	Ba3	BB-	BB-	13
	B1	B+	B+	14
Low grade	B2	B	B	15
	B3	B-	B-	16
	Caa1	CCC+	CCC+	17
	Caa2	CCC	CCC	18
	Caa3	CCC-	CCC-	19
	Ca	CC	CC	20
	C	C	C	21

Appendix B: Variable definitions

RATING is the assigned numeric rating score following Cheng and Neamtiu (2009).

EDF is the monthly expected default probability derived from the Merton/KMV model.

PILOT is an indicator variable that takes one if a firm' stock is a pilot stock under Regulation SHO's pilot program and zero otherwise.

DURING is an indicator variable that takes one if a rating is issued between May 2005 and June 2007 and zero if a rating is issued between May 2000 and June 2002.

DURING_b is an indicator variable that takes one if a rating is issued between August 2004 and April 2005 and zero if a rating is issued between May 2000 and June 2002.

POST is an indicator variable that takes one if a rating is issued between August 2007 and September 2009 and zero otherwise.

SP_RATING is an indicator variable equal to one if the rating agency is Standard & Poor's and zero if the rating agency is Moody's or Fitch.

FT_RATING is an indicator variable equal to one if the rating agency is Fitch and zero if the rating agency is Moody's or Standard & Poor's.

ISSUER_SIZE is the natural log of an issuer's total assets.

LEV is long-term debt divided by total assets.

OPMARGIN is operating income before depreciation divided by sales.

RETSTD is the standard deviation of daily stock returns for the fiscal year ending prior to the rating announcement dates.

ISSUE_SIZE is the natural log of the face value of the bond issue.

MATURITY is the natural log of the number of years until maturity.

SENIOR is an indicator variable equal to one if a bond has seniority status and zero otherwise.

SHORT is the number of shares shorted (set to zero when missing) divided by the number of shares outstanding.

DEFAULT_3YR is an indicator variable that equals one if a default event occurs within three years of the rating date and zero otherwise.

SALE is the natural log of sales.

CASH is cash divided by total assets.

ROA is operating income before depreciation divided by total assets.

CAP_INTEN is the net property, plant and equipment divided by total assets.

DAYAHEAD is the natural log of the number of days between the default date and the last speculative-grade, nondefault rating assigned on or before the default date.

WRATE is the sum of all rating levels outstanding during the one year leading to default multiplied by the number of days each rating has been outstanding, and then scaled by 365.

ABACC is the difference between actual accruals and the performance-adjusted (fitted) normal accruals based on the modified Jones (1991) model. When constructing the performance-adjusted normal accruals, we first estimate the following model cross-sectionally for industry-years with at least 15 observations:

$$TACC_t/TA_{t-1} = \beta_0 + \beta_1(1/TA_{t-1}) + \beta_2(\Delta Sales_t/TA_{t-1}) + \beta_3(PPE_t/TA_{t-1}) + \beta_4(ROA_{t-1})$$

where *TACC* is total accruals for the period t, *TA* is the total assets for the period t-1, *ΔSALES* is change in sales revenues for the period t, *PPE* is gross property and equipment for period t, and *ROA* is the return on assets during period t-1. Then we use the estimated coefficients and the following model to generate the performance-adjusted abnormal accruals:

$$TACC_t/TA_{t-1} = \beta_0 + \beta_1(1/TA_{t-1}) + \beta_2[(\Delta Sales_t-\Delta AR_t)/TA_{t-1}] + \beta_3(PPE_t/TA_{t-1}) + \beta_4(ROA_{t-1})$$

where ΔAR is the change in accounts receivable.

RESTATE is an indicator variable that takes a value of one if the firm has a financial statement restatement for the fiscal year ending prior to the rating announcement dates.

PRECISION is the average precision of a firm's quarterly management earnings forecasts, where forecast precision equals 0 if no forecast is issued, 1 for qualitative forecasts, 2 for range forecasts, and 3 for point forecasts.

DISCLOSURE is the natural log of one plus the product of *MF*, *FREQUENCY*, and *PRECISION*, where *MF* is an indicator variable equal to 1 if the firm issues management earnings forecasts, and 0 otherwise; *FREQUENCY* is the frequency of quarterly earnings forecasts provided by a firm over a fiscal year; *PRECISION* is defined above. When a firm has no management forecast, we set *DISCLSOURE* to be zero.

NANAL is the natural log of one plus the number of analysts following a company (set to zero when missing).

AF_ACCURACY is the absolute value of the difference between actual earnings and median consensus earnings forecast and then multiplied by negative one (scaled by the stock price at the end of the prior year).

VOLATILITY is the standard deviation of credit rating levels observed during the yearly window from May 1 to April 30 of the next year. Requires a minimum of three outstanding ratings during the yearly window.

COV is operating income before depreciation divided by interest expense.

NEG_RET is an indicator variable equal to one if a firm reports negative retained earnings and zero otherwise.

COVN is an indicator variable equal to one if the issue can be converted to the common stock of the issuer and zero otherwise.

ENHANCE is an indicator variable equal to one if the issue has a credit enhancement feature and zero otherwise.

PUT is an indicator variable equal to one if the issue has the option, but not the obligation, to sell the security back to the issuer and zero otherwise.

REDEEM is an indicator variable equal to one if the issue is redeemable under certain circumstances and zero otherwise.

RATELAG is credit rating right before the yearly window measurement date.

SPREAD is logged interest spread over LIBOR, in basis points, inclusive of fees. DealScan variable All_In_Drawn.

PP_RATING is an indicator that takes one if the loan has a rating-based performance-pricing provision and zero otherwise. Requires nonmising data in the DealScan performance pricing file.

ROA_b is income before extraordinary items scaled by total assets.

SECURED is an indicator if the loan is backed by collateral.

REVOLVER is an indicator for revolving loans.

RELATION is an indicator if one of the lead arrangers was a lead arrangers for the same borrower within the last five years.

LOAN_MATURITY is natural log of loan maturity in months.

LOAN_SIZE is natural log of the loan amount.

LENDERS is count of lenders participating in the loan.

INST_INVST is an indicator if the loan's type is term loan B, C, or D.

Table 1 Summary statistics - rating informativeness sample

This table presents the descriptive statistics for variables used in the main analyses for rating informativeness. All variables are defined in Appendix B.

	Mean	Median	0.250	0.750	Std
RATING	9.830	9.000	7.000	12.000	3.734
EDF	0.069	0.000	0.000	0.002	0.201
PILOT	0.308	0.000	0.000	1.000	0.462
DURING	0.408	0.000	0.000	1.000	0.491
SP_RATING	0.375	0.000	0.000	1.000	0.484
FT_RATING	0.281	0.000	0.000	1.000	0.449
ISSUER_SIZE	9.323	9.430	8.389	10.132	1.398
LEV	0.306	0.281	0.199	0.378	0.154
OPMARGIN	0.194	0.160	0.106	0.254	0.137
RETSTD	0.025	0.024	0.017	0.031	0.011
ISSUE_SIZE	12.519	12.612	12.117	13.122	1.143
MATURITY	1.960	2.007	1.405	2.819	1.046
SENIOR	0.845	1.000	1.000	1.000	0.361
SHORT	0.028	0.016	0.007	0.036	0.036

Table 2 Correlations - rating informativeness sample

This table presents correlations for variables used in the main analyses for rating informativeness, where the lower triangle presents Pearson correlations, while the upper triangle presents the Spearman correlations. All variables are defined in Appendix B. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

		A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*
RATING	*A*		0.336***	-0.010	0.249***	0.027***	-0.126***	-0.344***	0.469***	-0.225***	0.246***	-0.046***	-0.066***	-0.286***	0.184***
EDF	*B*	0.26***		-0.090***	-0.446***	0.051***	-0.159***	0.016**	0.273***	-0.133***	0.577***	-0.101***	-0.001	-0.119***	-0.018***
PILOT	*C*	-0.03***	-0.05***		0.002	-0.007	0.033***	-0.142***	-0.011*	0.055***	-0.038***	-0.080***	-0.026***	0.027***	0.069***
DURING	*D*	0.26***	-0.10***	0.00		-0.105***	0.188***	0.036***	-0.028***	-0.059***	-0.610***	0.169***	0.003	0.062***	0.148***
SP_RATING	*E*	0.02***	0.00	-0.01	-0.10***		-0.484***	-0.080***	0.015**	-0.007	0.094***	-0.033***	0.014**	-0.033***	-0.027***
FT_RATING	*F*	-0.12***	-0.05***	0.03***	0.19***	-0.48***		0.139***	-0.057***	0.015**	-0.182***	0.100***	-0.014**	0.109***	0.043***
ISSUER_SIZE	*G*	-0.32***	0.16***	-0.15***	0.05***	-0.08***	0.14***		-0.144***	0.065***	-0.146***	0.400***	0.077***	0.279***	-0.203***
LEV	*H*	0.52***	0.16***	-0.01*	-0.01	0.01**	-0.06***	-0.17***		0.052***	0.151***	-0.081***	-0.011*	-0.180***	0.081***
OPMARGIN	*I*	-0.16***	-0.09***	0.09***	0.01	-0.01*	0.02***	-0.00	0.05***		-0.100***	0.046***	0.017***	0.040***	-0.073***
RETSTD	*J*	0.33***	0.31***	-0.04***	-0.52***	0.09***	-0.17***	-0.19***	0.26***	-0.12***		-0.098***	-0.059***	-0.162***	-0.008
ISSUE_SIZE	*K*	-0.01**	-0.07***	-0.01*	0.15***	-0.01	0.09***	0.27***	-0.06***	0.04***	-0.07***		0.056***	0.209***	-0.028***
MATURITY	*L*	-0.05***	-0.01	-0.03***	-0.01	0.02***	-0.02***	0.08***	-0.03***	0.03***	-0.05***	0.07***		0.065***	0.013**
SENIOR	*M*	-0.29***	-0.04***	0.03***	0.06***	-0.03***	0.11***	0.30***	-0.19***	0.03***	-0.18***	0.29***	0.05***		-0.011*
SHORT	*N*	0.28***	-0.02***	0.06***	0.18***	-0.01**	0.01	-0.20***	0.16***	-0.02***	0.06***	0.00	-0.00	-0.05***	

Table 3 The impact of short selling threat on credit rating informativeness

This table reports OLS regression results of the impact of short selling threat on credit rating informativeness as reflected in the responsiveness of credit ratings to expected credit risk. All variables are defined in Appendix B. Financial variables are measured at the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are robust to heteroskedasticity and clustered by issue. *T* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

	RATING	
	(1)	(2)
EDF × PILOT × DURING	**2.829***** **(4.16)**	**3.183***** **(6.38)**
EDF × PILOT	0.234 (0.39)	-0.844** (-2.09)
EDF × DURING	2.635*** (6.90)	1.685*** (6.73)
PILOT × DURING	-0.785*** (-4.22)	-0.167 (-1.35)
EDF	3.774*** (11.33)	1.912*** (8.26)
PILOT	0.124 (0.91)	-0.018 (-0.20)
DURING	1.761*** (11.97)	3.198*** (28.20)
SP_RATING		-0.287*** (-10.89)
FT_RATING		-0.805*** (-21.93)
ISSUER_SIZE		-0.705*** (-24.21)
LEV		7.644*** (33.68)
OPMARGIN		-4.128*** (-15.45)
RETSTD		113.297*** (29.80)
ISSUE_SIZE		0.295*** (9.59)
MATURITY		-0.100*** (-3.36)
SENIOR		-1.146***

		(-12.21)
SHORT		7.023***
		(7.67)
EDF × SHORT		3.537
		(0.95)
Constant	7.152***	6.947***
	(35.79)	(14.82)
N	24146	24146
Adj. R^2	0.247	0.665

Table 4 The disciplining mechanism through which short selling threat influences credit rating informativeness

This table presents the additional empirical results of the disciplining mechanism through which short selling threat influences credit rating informativeness. Panel A presents the results of cross-sectional analyses of the impact of short selling threat on credit rating informativeness; Panel B reports the results of the effect of short selling threat on credit rating informativeness using the subsample without short sales; Panel C reports the results of the effect of short selling threat on credit rating informativeness by using the period from the announcement date of Reg SHO to April 30, 2005 (right before the implementation date of Reg SHO) as the during period. All variables are defined in Appendix B. Financial variables are measured at the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are heteroskedasticity-robust and clustered by issue. *T* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

Panel A: cross-sectional analyses

	RATING					
	Fitch market share		Reliance on external financing		Firm size	
	High	Low	High	Low	High	Low
EDF × PILOT × DURING	**3.459***** **(4.52)**	**38.981***** **(3.74)**	**18.592***** **(5.60)**	**2.17** **(1.09)**	**29.187***** **(9.37)**	**3.375***** **(6.22)**
Controls & FEs	YES	YES	YES	YES	YES	YES
N	7518	8517	10193	10125	11204	11184
Adjusted R^2	0.645	0.731	0.683	0.657	0.681	0.608
Subsample comparison	p-value=0.001		p-value=0.000		p-value=0.000	

Panel B: analyses using the subsample without short sales

	RATING
EDF × PILOT × DURING	**3.068***** **(4.62)**
Controls & FEs	YES
N	4551
Adjusted R^2	0.66

Panel C: an alternative way to define the during period - from the announcement date of Reg SHO to April 30, 2005

	RATING	
	(1)	(2)
EDF × PILOT × DURING_b	**8.316***** **(3.26)**	**9.188***** **(3.40)**
SHORT		7.634*** (6.78)
EDF × SHORT		3.847 (0.95)
Controls & FEs	YES	YES
N	16595	16595
Adj. R^2	0.697	0.701

Table 5 Short selling threat and credit rating informativeness: additional controls for the effect of informational environment

This table reports the results of testing the impact of short selling threat on credit rating informativeness after controlling for the effect of earnings management, voluntary disclosure, and analyst forecast. All variables are defined in Appendix B. Financial variables are measured at the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are robust to heteroskedasticity and clustered by issue. *T* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

	Dependent variable: *RATING*					
	ADD_CONTROL=					
	ABACC	*RESTATE*	*PRECISION*	*DISCLOSURE*	*NANAL*	*AF_ACCURACY*
	(1)	(2)	(3)	(4)	(5)	(6)
EDF × PILOT × DURING	**3.026*****	**4.080*****	**43.314****	**2.070*****	**3.997*****	**3.150*****
	(6.19)	**(7.44)**	**(1.97)**	**(4.39)**	**(7.69)**	**(6.39)**
ADD_CONTROL	0.037	0.657***	-0.231***	-0.323***	-0.648***	-6.564***
	(0.07)	(8.05)	(-3.59)	(-11.62)	(-8.79)	(-8.07)
EDF × ADD_CONTROL	4.104	-1.690***	-0.147	-0.887***	-0.615*	6.443**
	(1.47)	(-6.71)	(-0.64)	(-6.65)	(-1.66)	(2.54)
Controls & FEs	YES	YES	YES	YES	YES	YES
N	15355	24146	11372	24146	24146	23822
Adjusted R^2	0.685	0.669	0.697	0.675	0.672	0.668

Table 6 Short selling threat and credit rating informativeness: alternative measures

This table reports the results of testing the impact of short selling threat on credit rating informativeness using alternative measures of credit rating informativeness. Panel A uses the ability of credit ratings to predict future default as a measure for credit rating informativeness, while Panel B uses credit rating timeliness. All variables are defined in Appendix B. Financial variables are measured at the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are robust to heteroskedasticity and clustered by issue. *T (Z)* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

Panel A: the ability of credit ratings to predict future defaults

	DEFAULT_3YR	
	(1)	(2)
RATING × PILOT × DURING	**0.268****	**0.628****
	(2.20)	**(2.13)**
RATING × PILOT	-0.467***	-0.758***
	(-4.82)	(-2.81)
RATING × DURING	-0.273***	-0.487*
	(-3.20)	(-1.84)
PILOT × DURING	-5.736***	-11.589***
	(-2.66)	(-2.91)
RATING	0.836***	0.921***
	(12.23)	(3.25)
PILOT	9.484***	13.775***
	(5.75)	(3.98)
DURING	9.851***	16.437***
	(4.40)	(4.12)
SP_RATING		-0.203*
		(-1.80)
FT_RATING		-0.271*
		(-1.91)
ISSUER_SIZE		-0.288
		(-0.62)
LEV		-2.283
		(-1.60)
OPMARGIN		1.464
		(0.67)
RETSTD		58.761***
		(3.42)
ISSUE_SIZE		0.332**
		(2.39)

MATURITY		-0.069
		(-0.50)
SENIOR		-0.682
		(-1.58)
SHORT		-6.295
		(-0.25)
RATING × SHORT		-1.368
		(-0.96)
SALE		-0.045
		(-0.10)
CASH		-14.218***
		(-4.35)
ROA		-10.733*
		(-1.73)
CAP_INTEN		1.468**
		(2.44)
Constant	-20.887***	-24.088***
	(-9.71)	(-4.56)
N	15436	15402
Pseudo R^2	0.442	0.565

Panel B: credit rating timeliness

	DAYAHEAD		*WRATE*	
	(1)	(2)	(3)	(4)
PILOT × DURING	**4.422*****	**3.886*****	**13.193*****	**11.412*****
	(6.84)	**(3.93)**	**(5.02)**	**(3.25)**
PILOT	-4.489***	-3.564***	-10.254***	-7.240*
	(-9.74)	(-3.42)	(-6.74)	(-1.89)
DURING	-0.188	-0.503	-0.288	9.307**
	(-0.34)	(-0.75)	(-0.18)	(2.31)
SP_RATING		0.442*		-0.331
		(1.91)		(-0.44)
FT_RATING		0.362		-0.633
		(0.95)		(-0.41)
ISSUER_SIZE		0.724**		1.171
		(2.43)		(0.83)
COV		0.013		0.132
		(0.68)		(1.40)
LEV		1.087		-8.887*
		(1.31)		(-1.89)

NEG_RET		0.235		2.595
		(0.68)		(1.24)
ISSUE_SIZE		-0.315		0.067
		(-1.66)		(0.10)
MATURITY		-0.262		1.189
		(-1.07)		(0.88)
SENIOR		-0.812**		-2.161
		(-2.22)		(-1.30)
CONV		-1.764***		-4.263
		(-3.09)		(-1.02)
ENHANCE		0.523*		-6.739***
		(1.93)		(-3.63)
PUT		0.536		2.641
		(0.67)		(0.66)
REDEEM		0.459		3.400*
		(1.11)		(1.97)
SHORT		-6.033*		-5.981
		(-1.92)		(-0.42)
Constant	6.088***	3.719	5.093**	-18.096*
	(8.75)	(1.37)	(2.42)	(-1.84)
N	141	141	125	125
Adj. R^2	0.335	0.437	0.229	0.413

Table 7 Short selling threat and credit rating informativeness: the permanent removal of the price tests

This table reports the results of the placebo tests for the effect of short selling threat on credit rating informativeness. All variables are defined in the Appendix. Financial variables are measured in the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are robust to heteroskedasticity and clustered by issue. *T* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

	RATING
EDF × PILOT × POST	**-0.977**
	(-1.60)
EDF × PILOT	-0.046
	(-0.11)
EDF × POST	**2.986*****
	(9.89)
PILOT × POST	0.216
	(1.47)
EDF	2.974***
	(12.05)
PILOT	0.001
	(0.01)
POST	0.872***
	(9.05)
Controls & FEs	YES
N	23453
Adjusted R^2	0.663

Table 8 The impact of short selling threat on credit rating volatility

This table presents the results of testing the impact of short selling threat on credit rating volatility. All variables are defined in Appendix B. Financial variables are measured at the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are heteroskedasticity-robust and clustered by issue. *T* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

	VOLATILITY	
	(1)	(2)
PILOT* × *DURING	**1.340****	**1.074****
	(2.33)	**(2.15)**
PILOT	0.008	0.098
	(0.04)	(0.55)
DURING	-0.457	-0.226
	(-1.01)	(-0.45)
SP_RATING		-0.191**
		(-2.32)
FT_RATING		-0.475***
		(-3.90)
ISSUER_SIZE		-0.077
		(-1.26)
COV		-0.006
		(-0.59)
LEV		-0.461
		(-0.76)
NEG_RET		-0.177
		(-0.62)
ISSUE_SIZE		0.043
		(0.70)
MATURITY		0.01
		(0.28)
SENIOR		0.016
		(0.13)
CONV		0.056
		(0.37)
ENHANCE		-0.280**
		(-2.10)
PUT		0.101
		(1.08)
REDEEM		-0.076
		(-0.88)

RATELAG		0.02
		(0.65)
SHORT		-4.818***
		(-3.17)
Constant	1.110***	1.899*
	(2.93)	(1.91)
N	1282	1282
Adj. R^2	0.36	0.426

Table 9 The impact of short selling threat on the use of credit ratings in debt contracts

This table presents the results of testing the impact of short selling threat on the use of credit ratings in debt contracts. Penal A identifies the rating use by utilizing the association between credit rating and the initial loan spread, while Panel B identifies the rating use by utilizing an indicator variable for the existence of rating-based performance pricing provisions. All variables are defined in Appendix B. Financial variables are measured at the fiscal year ending prior to the rating assignment dates. Standard errors for the coefficient estimates are heteroskedasticity-robust and clustered by issue. *T* statistics are reported in parentheses. Industry and year fixed effects are included in all regressions. * indicates significance at 10%, ** at 5%, *** at 1% level based on two-tailed tests.

Panel A: relation between credit rating and loan spread

	LOAN_SPREAD	
	(1)	(2)
RATING × PILOT × DURING	**-0.041***** **(-2.92)**	**-0.020**** **(-2.21)**
RATING × PILOT	0.020* (1.83)	0.021*** (2.97)
RATING × DURING	-0.036*** (-5.30)	-0.035*** (-7.49)
PILOT × DURING	0.611*** (3.44)	0.306*** (2.77)
RATING	0.152*** (29.62)	0.099*** (21.59)
PILOT	-0.378*** (-2.99)	-0.346*** (-4.42)
DURING	0.526*** (5.90)	0.485*** (7.60)
SP_RATING		-0.014** (-2.00)
FT_RATING		0.021** (2.02)
ISSUER_SIZE		0.085*** (12.43)
LEV		-0.164*** (-3.08)
ROA		-0.331*** (-2.75)
ISSUE_SIZE		-0.071***

		(-9.87)
MATURITY		-0.034***
		(-5.39)
SENIOR		0.111***
		(6.27)
SECURED		0.783***
		(37.99)
REVOLVER		-0.076***
		(-5.56)
RELATION		-0.166***
		(-13.82)
LOAN_MATURITY		-0.030***
		(-2.70)
LOAN_SIZE		-0.112***
		(-16.14)
LENDERS		-0.008***
		(-10.12)
INST_INVST		0.235***
		(15.79)
SHORT		0.329
		(0.49)
RATING × SHORT		-0.067
		(-1.41)
Constant	3.249***	6.131***
	(27.35)	(40.08)
N	30453	30453
Adj. R^2	0.39	0.661

Panel B: use of rating-based performance pricing provisions

	PP_RATING	
	(1)	(2)
PILOT × DURING	**-0.142*****	**-0.095*****
	(-3.90)	**(-3.71)**
PILOT	-0.035	0.049***
	(-1.39)	(2.88)
DURING	-0.119***	-0.049**
	(-3.66)	(-2.22)
SP_RATING		0.003
		(0.70)
FT_RATING		0.019***

		(2.77)
ISSUER_SIZE		0.040***
		(6.15)
LEV		-0.04
		(-0.83)
ROA_b		-0.172
		(-1.12)
ISSUE_SIZE		0.019***
		(2.66)
MATURITY		0.011**
		(2.47)
SENIOR		0.069***
		(4.00)
SECURED		-0.383***
		(-18.13)
REVOLVER		0.062***
		(4.95)
RELATION		0.037***
		(3.30)
LOAN_MATURITY		-0.084***
		(-8.88)
LOAN_SIZE		0.032***
		(5.60)
LENDERS		0.001
		(1.07)
INST_INVST		0.050**
		(2.18)
RATING		-0.022***
		(-7.07)
SHORT		0.448***
		(2.70)
Constant	0.712***	-0.119
	(12.81)	(-0.93)
N	17071	17071
Adj. R^2	0.145	0.557