Do Rating Agencies Behave Defensively for Higher Risk Issuers?*

Samuel B. Bonsall, IV†
The Pennsylvania State University

Kevin Koharki
Purdue University

Pepa Kraft
HEC Paris

Karl A. Muller, III
The Pennsylvania State University

Anywhere Sikochi
Harvard University

February 28, 2022

Abstract

We examine whether rating agencies act defensively toward issuers with a higher likelihood of default. We find that agencies' qualitative soft rating adjustments are more accurate as issuers' default risk grows, as evidenced by the adjustments leading to lower Type I and Type II error rates and better prediction of default and default recovery losses. We also find that soft adjustments' relevance increases with issuers' default risk, as evidenced by the adjustments being more predictive of initial offering yields and leading to a greater market reaction to rating changes. Further, we find that the rating agencies assign better educated and more experienced analysts to higher risk issuers, providing evidence of one mechanism used by the rating agencies to generate more accurate and relevant soft adjustments. Overall, our study suggests that as the likelihood of issuer default grows the threat of reputational harm from discovered rating failures increasingly mitigates the rating agencies' strategic behavior incentivized by the issuer-pay model.

JEL classification: G24, G32, G33
Keywords: credit rating agencies; soft rating adjustments; default

*The authors thank Sanjeev Bhojraj (discussant), Lauren Cohen, Paul Fischer, Paul Healy, John Jiang, Monica Neamtiu, Ed Owens (discussant), David Yu, and Mina Zarrin, as well as workshop participants at the AAA Annual Meeting, Information, Markets, and Organizations Conference at the Harvard Business School, PwC Young Scholars Research Symposium at the University of Illinois, UCLA, and the Wharton School for helpful comments and Moody's Investors Service for assistance with its Default and Recovery Database. The authors thank the Harvard Business School, HEC Paris, Krannert School of Management, and Smeal College of Business. Kraft and Muller also gratefully acknowledge funding received from HEC Paris Foundation and Labex Ecodec (ANR-11-LABX-0047) and the Poole Faculty Fellowship, respectively. In addition, the authors thank Cesare Fracassi, Stefan Petry, and Geoffrey Tate for generously sharing their demographic trait data on individual credit rating analysts.

†Corresponding Author. Address: 385 Business Building, University Park, PA 16802. Telephone number: 814-865-4572. Fax number: 814-863-8393. Email address: sbb151@psu.edu.

Do Rating Agencies Behave Defensively for Higher Risk Issuers?

Abstract

We examine whether rating agencies act defensively toward issuers with a higher likelihood of default. We find that agencies' qualitative soft rating adjustments are more accurate as issuers' default risk grows, as evidenced by the adjustments leading to lower Type I and Type II error rates and better prediction of default and default recovery losses. We also find that soft adjustments' relevance increases with issuers' default risk, as evidenced by the adjustments being more predictive of initial offering yields and leading to a greater market reaction to rating changes. Further, we find that the rating agencies assign better educated and more experienced analysts to higher risk issuers, providing evidence of one mechanism used by the rating agencies to generate more accurate and relevant soft adjustments. Overall, our study suggests that as the likelihood of issuer default grows the threat of reputational harm from discovered rating failures increasingly mitigates the rating agencies' strategic behavior incentivized by the issuer-pay model.

JEL classification: G24, G32, G33
Keywords: credit rating agencies; soft rating adjustments; default

1. Introduction

Major credit rating agencies have been repeatedly criticized over the past two decades for failing to provide timely and accurate warnings to debt market participants about high risk issuers. Some have argued that rating agencies lack sufficient incentives to monitor issuers because of heavy regulatory reliance on credit ratings since the mid-1970s (see, for example, Partnoy, 1999; Partnoy, 2010). Others have blamed the agencies' issuer-pay business model for facilitating an economic bond with issuers, and research finds that the issuer-pay model encourages optimistic ratings (e.g., He, Qian, and Strahan 2012; Jiang, Stanford, and Xie 2012; Xia and Strobl 2012; Bruno, Cornaggia, and Cornaggia 2016; Cornaggia and Cornaggia 2013; Xia 2014; Efing and Hau 2015; Baghai and Becker 2020). The opposing view—one espoused by the rating agencies—is that the need to maintain a strong reputation outweighs the incentive issues raised by critics.

In this study, we broadly examine this position by examining whether rating agencies use their discretion defensively for higher expected default risk issuers to provide more accurate and relevant signals to the market and maintain their reputations. Why would rating agencies behave defensively for higher risk issuers, despite the numerous examples of misses noted by critics and incentives that may lead to the lax monitoring of issuers and sluggish responses to changes in credit risk? As analytically shown by Bolton, Freixas, and Shapiro (2012), when an investment fails, the credit rating agency will not be punished by investors if they believe that a rating agency acted in good faith when receiving information. However, if investors believe that the rating agency catered to the client and reported falsely, then they will punish the rating agency for the "rating failure" by lowering their reliance on the rating agency. This reduction in future demand for its services will lead to lower future economic rents for the rating agency. Prior research corroborates the existence of this reputational cost. Bonsall, Green, and Muller (2018) provide evidence that rating agencies receive a lower proportion of rating engagements for new issuances following missed defaults of issuers in the same industry, especially for more visible issuers. In addition, deHaan (2017) finds reduced investor reliance on corporate issuers' ratings following the financial crisis, consistent with spillover in the reputational damage to the rating agencies from collateralized debt obligations (CDOs) and mortgage-backed securities (MBSs) rating failures. Because of rating agencies' access to issuers' private information when the issuer is a going concern, the detection of rating inflation by investors is generally only observable when default occurs. This generates an incentive for rating agencies to become more defensive toward issuers who have a higher likelihood of default (Vazza and Kraemer, 2016). The costs of rating failures can also arise from reduced regulatory reliance on ratings, greater regulatory oversight, and potential legal liability. However, whether these potential reputational harm and other costs are sufficient to mitigate incentives created by the issuer-pay model is unclear.

Using corporate issuers from 2003–2015, we examine whether rating agencies use discretion in reported ratings to behave more defensively toward issuers with higher default risk. Our analysis focuses on two broad attributes of credit ratings: accuracy and investor relevance. The rating agencies (e.g., Cantor and Mann, 2003) and academics have focused on these attributes when examining the overall quality of credit ratings.[1] An empirical challenge in studying our research question is that issuers' credit risk and rating attributes may both be a function of unobservable issuer characteristics that are correlated with rating agencies' reputational concerns. To overcome this empirical challenge and provide evidence that the actions of credit rating agencies are strategic, we separately examine Moody's grid-based ratings, which are largely objective as they are based on common financial ratios and standard hard (quantitative) adjustments, and Moody's soft rating adjustments, which are largely subjective qualitative adjustments made by rating committees (Kraft, 2015b). Our approach is similar to that used by Griffin and Tang (2012) to examine the strategic use of rating adjustments to inflate CDO ratings to AAA in the period prior to the financial crisis and by Kraft (2015a) to examine the strategic use of Moody's soft rating adjustments for issuers with ratings-based performance pricing in lending contracts.

To strengthen our inferences, we examine whether our findings of defensive behavior are more pronounced in the years following the 2008 global financial crisis and for issuers that receive greater media attention. The global financial crisis led to mass declines in the ratings of MBSs and CDOs. deHaan (2017) provides evidence that the reputational harm caused by problems with MBS and CDO ratings spilled over to corporate ratings, resulting in rating agencies improving the quality of corporate ratings following the crisis. In addition, Bonsall et al. (2018) find that rating agencies assign more timely and accurate ratings for more visible issuers. Rating agencies face incentives

[1] See Alp (2013), Cornaggia and Cornaggia (2013), Baghai, Servaes, and Tamayo (2014), Bruno et al. (2016), and Fracassi, Petry, and Tate (2016) for examples of academic studies and how they have measured the attributes of credit ratings.

to issue higher quality ratings for such issuers. First, issuers are subject to greater scrutiny by market participants, which can lead to greater detection of inaccurate ratings. Second, information about rating failures will be more widely disseminated to market participants. Both can lead to reputational harm to a rating agency and, as Bonsall et al. (2018) find, a loss in the future rating opportunities for new issuances.

Regarding accuracy, we find that the rate of Type I errors (i.e., missed defaults) is lower for issuers with greater pre-default credit risk, with the results being attributable to soft rating adjustments.[2] In addition, we find that the rate of Type II errors (i.e., false default predictions) is lower for issuers with greater default risk—and again attributable to subjective soft rating adjustments. Using Moody's Default and Recovery Database (DRD), we also find that the ability of soft rating adjustments to predict default one and three years ahead increases for issuers with higher default risk. Further, we find that soft rating adjustments are more predictive of default recovery losses for issuers with greater pre-default credit risk. This evidence is important, as recovery rate estimation requires extensive judgment about the interplay among capital structure, creditor rights, jurisdiction, state law, and other forces in determining liquidation payouts. In all these analyses, we find that the results are more pronounced in the years after the financial crisis and for issuers that receive greater media coverage. Collectively, these results provide evidence that major credit rating agencies use discretion over the rating process to defensively assign more accurate ratings for higher credit risk issuers.

Regarding investor relevance, we find that soft rating adjustments better explain initial offering yields when issuers' expected default risk is higher. In addition, we find that the stock market reaction to rating downgrades is incrementally stronger for downgrades that result solely from soft rating adjustments as default risk increases. This finding suggests that soft rating adjustments reveal private information and do not simply reflect public information already known to financial markets. We fail to find similar evidence for rating upgrades, consistent with prior research finding that upgrades typically provide less information to financial markets (e.g., Holthausen and Leftwich, 1986). Further, we find that the market reaction to downgrades is more pronounced in the post-

[2]Although we use Moody's ratings, we generalize our results to "rating agencies" because of the notion that the leading credit rating agencies are relatively homogenous and that Moody's and S&P are reasonable substitutes (e.g., Holthausen and Leftwich, 1986; Dichev and Piotroski, 2001; Beaver, Shakespeare, and Soliman, 2006; Bonsall, Koharki, and Neamtiu, 2017; Hung, Kraft, Wang, and Yu, forthcoming).

financial crisis period and for more widely covered issuers.

Our last set of tests examines an important channel through which rating agencies can achieve more accurate and relevant ratings—the strategic assignment of better credit analysts. Consistent with this possibility, we find that better educated analysts (i.e., analysts holding a Master of Business Administration (MBA) degree, especially from a top MBA program) are more likely to be assigned to issuers with higher expected default risk. In addition, we find that analysts who are older, have longer tenure in the industry and with the rating agency, and cover a larger number of issuers are more likely to be assigned to issuers with higher expected default risk.

Our findings provide several contributions to the credit rating literature. First, we provide evidence that the rating agencies behave consistently with economic incentives modeled by Bolton et al. (2012) to assign ratings more conservatively for issuers with higher expected default risk. These incentives lead to important improvements in ratings, including ratings becoming more accurate and relevant through rating agencies revealing more of their private information. Moreover, our finding of an improvement in rating quality before instances of issuer default suggests that these rare events provide strong incentives for agencies to assign higher quality ratings (i.e., issuer defaults are closely scrutinized by various market participants such as investors, competitors, regulators, and the media). Consistent with the improvements being discretionary, we find that the changes are attributable to subjective soft rating adjustments, rather than grid-based ratings, and that our results are more pronounced in the post-financial crisis period when the rating agencies are attempting to rebuild their damaged reputations (deHaan, 2017) and for more widely followed issuers that pose greater reputational risk for rating agencies (Bonsall et al., 2018). These findings provide the first evidence supporting the Bolton et al. (2012) proposition that the costs associated with a rating failure—which can typically only be assessed at issuer default given that rating agencies possess private information during other times—can lead to higher quality ratings when the probability of rating agencies "getting caught" grows. The reputational harm from getting caught can lead to investors lowering their use of the services of the rating agency, as predicted by Bolton et al. (2012), as well as reduced regulatory reliance on ratings, and greater regulatory oversight and possibly legal liability. Together, this evidence suggests that the threat of detection costs arising from rating failures can mitigate some of the opportunistic incentives created by the issuer-pay model. From a regulatory perspective, our evidence suggests that broad-based regulations such as those imposed through the Credit Rating Agency Reform Act of 2006 and Dodd-Frank Wall Street and Consumer Protection Act of 2010 should consider rating agencies' tendency to behave more defensively toward issuers with higher expected default risk.

Second, we provide evidence that contributes to the growing literature on how the credit rating agencies strategically assign ratings across different rating levels. Related research has exclusively focused on showing that ratings are opportunistically assigned higher at important rating thresholds to cater to issuers. In one important setting, several studies show evidence of strategic behavior at the investment-grade threshold.[3] For instance, Beaver et al. (2006) find that Moody's, a rating agency certified by the Securities and Exchange Commission (SEC), is more reluctant than Egan-Jones, a non-SEC-certified rating agency, to downgrade clients to below investment-grade, consistent with Moody's being more cautious because of its ratings' use in contracting.[4] In addition, Jiang et al. (2012) provide evidence that first time adoption of the issuer-pay model in the 1970s led to the issuance of more favorable ratings, especially for clients at the investment-grade threshold. Notably, in contrast, Bonsall (2014) provides evidence that credit ratings became more timely, accurate, and informative following the switch to the issuer-pay model, which raises the possibility that the more favorable ratings observed by Jiang et al. (2012) are attributable to more favorable private information about future performance rather than client catering. More recent studies provide further evidence of catering at the investment-grade threshold (e.g., Alp, 2013; Kraft, 2015a; Kedia, Rajgopal, and Zhou, 2017). In another important threshold setting, prior research shows that ratings are used to cater to clients when they are near the AAA threshold for CDOs. Griffin and Tang (2012) find that just prior to the financial crisis, the rating agencies lowered their standards to cater to clients by making positive rating adjustments, leading to a greater number of AAA CDO tranches for clients. Our findings complement these prior findings by showing that while behavior consistent with incentives under the issuer-pay model exist in settings where those incentives are most pronounced, credit rating agencies broadly assign ratings across different rating levels not to cater to client interests but rather to behave defensively to limit po-

[3]Some studies also use the investment-grade and speculative-grade debt distinction as a control variable or as a sensitivity test (e.g., Baghai and Becker, 2018; Bonsall et al., 2017; Sethuraman, 2019).

[4]A rating downgrade to below the investment-grade threshold can lead to clients facing significant costs (e.g., selling of bonds by banks, insurance firms, broker-dealers, and pension funds due to restrictions on holding speculative-grade bonds, increased interest rates in performance-priced contracts, and lower ability to raise new capital). Consistent with greater costs for such downgrades being costlier, Jorion, Liu, and Shi (2005) find that the market reaction for downgrades is greater when ratings move from investment-grade to speculative-grade.

tential reputational and economic harm when rating those issuers of greatest concern to investors and regulators.

Third, we add to the accounting literature exploring how credit agencies use soft rating adjustments (Kraft 2015b; Kraft 2015a). Kraft (2015b) finds that soft rating adjustments are a large component of credit ratings and are associated with credit spreads, increasing the relevance of ratings to users. Kraft (2015a) provides evidence that higher soft adjustments are used to cater to issuers with performance pricing provisions, with the catering being muted for issuers near the investment grade threshold and rated by Fitch. Our findings go beyond those at the investment-grade cutoff observed by Kraft (2015a), as the investment-grade cutoff does not necessarily translate to other rating levels. In addition, evidence at the investment-grade cutoff does not provide a clear test of the predictions of Bolton et al. (2012) because so few issuers at the investment-grade cutoff actually default and incentives under the issuer pay model dominate rating agencies' behavior.

Finally, our evidence contributes to recent research on the ongoing monitoring by rating agencies. Bonsall, Koharki, and Neamtiu (2015) find that credit rating agencies engage in lax borrower monitoring post issuance, as the attention of various participants engaged before and during a bond's offering (e.g., underwriters, regulators, and legal representatives) subsides over time. Our findings suggest that rating agencies' assignment of soft rating adjustments for higher risk issuers leads to ratings that are more relevant and reveal more of rating agencies' private information, suggestive of continued monitoring and enhanced information production.

2. Primary variables, identification strategy, and sample

This section discusses qualitative soft rating adjustments and grid-based ratings, as well as our other primary variable: issuer expected default frequency. We then discuss our identification strategy, describe the data sources used for our empirical tests, and provide summary statistics for variables used in the analyses.

2.1. Qualitative soft rating adjustments

Moody's Financial Metrics, our source of disaggregated ratings data, creates different inputs to determine reported credit ratings. To illustrate how this is accomplished, we depict the different components of credit ratings in Figure 1. First, Moody's relies on a scorecard based on an industry-specific set of quantitative factors and weights for each factor. The quantitative set of factors can be large and typically includes financial ratios based on reported generally accepted accounting principles (GAAP) amounts (e.g., scale, profitability, cash flow, leverage, coverage, and efficiency).

Moody's then normally makes hard and soft adjustments to arrive at its actual ratings.[5] Hard adjustments are typically quantitative-based adjustments to reported GAAP numbers used to calculate standard financial ratios. These adjustments include standard adjustments for underfunded defined benefit plans, operating leases, capitalized interest, employee stock compensation, hybrid securities, securitizations, inventory on a last-in first-out (LIFO) cost basis, and unusual and non-recurring items (Moody's Investors Services, 2006). These quantitative hard adjustments can be based on public and private information. As shown in Figure 1, the combination of the model-based rating with the hard adjustments is the grid-based rating. The last adjustments are soft rating adjustments. These adjustments account for certain qualitative aspects of the issuer, such as the quality of management, governance, internal controls, and other internal and external factors that could affect the issuer's creditworthiness. These adjustments can also be based on public and private information.[6] Similar to hard adjustments, these soft adjustments are given a numerical score. Unlike hard adjustments, which are largely algorithmic adjustments to reported GAAP numbers, soft adjustments contain considerable discretion because of the subjectivity of the types of items being evaluated (e.g., the quality of management).[7] The reported rating is the sum of the

[5]In some instances these adjustments lead to more conservative amounts. For instance, Batta and Muslu (2017) show that Moody's adjustments to GAAP earnings lead to a more conservative measure of performance. In addition, Kraft (2015b) provides evidence that the most important adjustments relate to the inclusion of off-balance-sheet debt, which typically leads to significant increases in issuers' leverage ratios.

[6]Bozanic, Kraft, and Tillet (forthcoming) demonstrate that some soft adjustments reflect managers' discussions in public financial disclosures.

[7]To the extent that information is disclosed by issuers—even if not recognized on the face of the financial statements—credit rating agencies (at least Moody's) will typically incorporate the credit risk implications of the disclosed information as a quantitative adjustment to the GAAP ratio implied credit rating. Quantitative adjustments for leases are such an example. Alternatively, if Moody's obtains material nonpublic information about off-balance sheet leverage, the credit risk implications of that leverage are more likely to show up as a soft rating adjustment. A plausible example of a significant shift in soft adjustments was around 2003 when FIN 46 significantly increased the disclosure of off-balance sheet arrangements that were recognized as variable interest entities. If Moody's had been incorporating this information in ratings prior to FIN 46, it would likely have shifted from soft adjustments to quantitative adjustments following FIN 46.

Beyond changes to the nature of credit rating agencies' information set, soft adjustments could change over time because of general shifts in reputational, regulatory, or litigation concerns. The results in Alp (2013), Baghai et al. (2014), and Cheng and Neamtiu (2009) around the Enron bankruptcy are generally consistent with this notion—even though they do not directly examine soft adjustments—as are the results in deHaan (2017) and Dimitrov et al. (2015) around the global financial crisis.

grid-based rating score and the soft rating adjustment score.

Soft rating adjustments can be used opportunistically to inflate ratings, particularly when one considers the difficulty in estimating default and recovery rates or, alternatively, can also be used to convey information. Given the increased reputational costs from overrating high-risk issuers, we predict that rating agencies will use soft adjustments to issue ratings that are more accurate and relevant for such issuers.

2.2. Measuring default risk: Expected default frequency

To capture default risk, the other primary variable in our tests, we use expected default frequency (EDF) as a proxy. We estimate EDF following the Merton (1974) model using the approach in Hillegeist, Keating, Cram, and Lundstedt (2004). Similar to related research (e.g., Kedia, Rajgopal, and Zhou, 2014; Xia, 2014; Bonsall et al., 2015; Fracassi et al., 2016; Kedia et al., 2017), we use this market-based measure of default risk, which is less likely than actual ratings to reflect the strategic behavior of rating agencies. However, the EDF measure has an important limitation. Bharath and Shumway (2008) demonstrate that the estimated default probabilities of the Merton (1974) model have a limited ability to explain bond yields in the presence of actual credit ratings. This can be attributed to the EDF measure being somewhat imprecise because of a failure to meet the strict assumptions of the Merton (1974) model. Accordingly, the use of EDF could lower the ability of our tests to detect differences in issuer default risk.

2.3. Identification strategy

To strengthen our inferences, we exploit two distinct settings when the rating agencies should face greater scrutiny: the post-financial crisis period and when the issuer is more prominent and visible. The 2008 global financial crisis exposed a failure in the ratings of MBS and CDO instruments. In the aftermath of the crisis, rating agencies attempted to salvage their reputations from the damage caused by the rating failures in the MBS and CDO markets. Consistent with this, deHaan (2017) finds that the quality of corporate ratings improved following the financial crisis. Building on deHaan (2017), we examine whether soft rating adjustments are relatively more accurate and relevant for issuers with higher expected default risk following the financial crisis. For these analyses, we use $PostCrisis$, an indicator variable equal to one for ratings existing on or after July 1, 2009, and zero otherwise.

In addition, Bonsall et al. (2018) provide evidence that the greater prominence and visibility of issuers brought about by more widely covered issuers creates reputational risk for rating agencies in the event of a rating failure.[8] Specifically, Bonsall et al. (2018) find that ratings are more timely and accurate and, for defaulting issuers, are associated with more timely downgrades and systematically lower ratings prior to default. Following Bonsall et al. (2018) we further investigate whether soft rating adjustments are relatively more accurate and relevant for issuers with greater media coverage. We conduct the analysis using $LMediaCov$, which is the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date.

2.4. Sample selection

We generate distinct samples corresponding with various measures of the two broad attributes of credit ratings that are our focus: accuracy and investor relevance. In addition, we generate a sample for our analysis on credit rating analysts' assignments. The analyses for the accuracy of ratings require four samples. Our first sample comprises defaulting bonds for our analysis of the frequency of Moody's Type I errors (i.e., missed default predictions). As shown in Panel A of Table 1, we obtain data on default events from Moody's DRD, derived from Moody's proprietary database of issuer, default, and recovery information. We then merge our baseline sample of Moody's default ratings with data from the Mergent Fixed Income Securities Database (FISD) to provide control variables from Cheng and Neamtiu (2009) and other related studies. This sample covers issuer-years between 2003 and 2015 and requires the availability of EDF. Observations are lost due to missing Compustat GVKEY and missing Compustat coverage in the preceding fiscal year, no coverage of the bond by Moody's Investors Service or Moody's Financial Metrics, and insufficient data to compute EDF. The resulting sample for the Type I error analysis comprises 792 observations at the issue-default level, which relate to 537 unique issuers.

Our second sample relates to our analysis of the frequency of Moody's Type II errors (i.e., false

[8] We also considered using issue size, issue frequency, and issuer market capitalization as visibility measures. We do not use issuer size and issue frequency, as they could alternatively serve as proxies for rating agencies' incentives to cater to issuers. We do not use issuer market capitalization, as firm size does not necessarily lead to greater visibility in the debt market and is correlated with factors that could confound our analysis.

default predictions) for non-defaulting issuers. As shown in Panel A of Table 1, the sample for this analysis consists of all issue-year observations for which we have Moody's grid-based ratings and soft rating adjustments from Moody's Financial Metrics and which do not default in the following 12 months. After requiring information for the control variables from Cheng and Neamtiu (2009), the Type II error sample comprises 90,186 observations at the issue-year level. Observations are lost due to similar reasons as for our Type I sample (e.g., missing Compustat coverage).

We do not tabulate the steps involved in constructing the third and fourth samples, as the steps are similar and less extensive. The third sample relates to our analysis of default prediction, requiring issuer-year observations for both defaulting and non-defaulting issuers. After requiring information for the control variables from Becker and Milbourn (2011) and Moody's grid-based ratings and soft rating adjustments, the default prediction sample comprises 5,432 observations at the issuer-year level.

The fourth sample relates to our analysis of default recovery losses. We obtain data on default events from the Moody's DRD, which provides default dates, price at default (i.e., creditor recovery rates), and several characteristics of the defaulted debt instruments such as default type, default event description, default history, debt seniority, debt type, and coupon rate. To identify issuers in default, we start with defaults for corporate entities across all industries in the master default table and then limit our sample to default events for U.S. publicly traded industrial issuers and default types identified as distressed exchanges, Chapter 11 (re-organization) bankruptcy, and missed payments on interest or principal. Our final sample that examines soft rating adjustments and default recoveries includes 351 observations at the issue-default level for which we have Moody's grid-based ratings and soft rating adjustments.

The analyses for the relevance of ratings require two samples. The first sample is for our analysis examining the association between ratings and offering yield spreads. This sample consists of issue-level observations for newly issued non-convertible, fixed rate bonds from the Mergent FISD during our 2003–2015 sample period. After requiring information for all the issuer and issue-related control variables, along with Moody's grid-based ratings and soft rating adjustments, the offering yield sample contains 2,455 observations at the issue level.

The second sample relates to our analyses investigating how equity returns predict rating changes and examining the response of equity investors to rating changes as a function of credit risk. We collect rating upgrade and downgrade information from Moody's. In cases of multiple rating changes per issuer on a given day, we retain the largest magnitude rating change, consistent with the procedure used by Jorion et al. (2005). After requiring Moody's grid-based ratings and soft rating adjustments, along with equity returns over the required windows prior to the rating change events, the sample contains 1,714 downgrades and 1,490 upgrades at the issue-rating change level.

For our final analysis of whether rating agencies strategically assign higher quality credit analysts to higher risk issuers, we use data from Fracassi et al. (2016). We retain issuer-quarters from Fracassi et al. (2016) representing Moody's analysts for which we also have Moody's grid-based ratings and soft rating adjustments. We then merge this subset of observations with the control variables from our Type II error sample. Our credit analyst quality sample contains 4,883 issuer-quarter observations.

2.5. Descriptive statistics

Panel B of Table 1 provides summary statistics for the variables used in our Type I and Type II analyses, as they are the broadest samples for defaulting and non-defaulting issuers. This panel also provides a formal test of differences in medians for high and low EDF groups. The key variables in the Type I error sample are $SoftAdjustAvoidE_{TypeI}$ (an indicator variable equal to one if the Moody's soft rating adjustments ($SoftAdj$) *avoids* an otherwise missed default indicated by the grid-based rating, and zero otherwise) and $E_{TypeI,AdjustedGrid}$ (an indicator variable equal to one if the grid-based quantitative rating *fails* to predict an actual event of default for a bond issue based on a cutoff rating of Baa3, and zero otherwise). $SoftAdjustAvoidE_{TypeI}$ and $E_{TypeI,AdjustedGrid}$ have means of 0.323 and 0.442, respectively, consistent with grid-based ratings leading to higher Type I errors than those related to soft rating adjustments. The difference in means test indicates that soft rating adjustments reduce Type I errors to a greater extent for above-median EDF issuers than for below-median EDF issuers. We fail to find a difference between the high and low EDF groups for $E_{TypeI,AdjustedGrid}$. For the Type II error sample, the variables of interest are $SoftAdjustAvoidE_{TypeII}$ (an indicator variable equal to one if $SoftAdj$ avoids an otherwise falsely identified default indicated by the grid-based rating, and zero otherwise) and $E_{TypeII,AdjustedGrid}$ (an indicator variable equal to one if the grid-based quantitative ratings falsely predicted default based on a cutoff rating of Baa3 for a bond issue, and zero otherwise). These variables have means of 0.078 and 0.260, respectively. This is also consistent with grid-based ratings leading to higher rating errors than ratings related to soft rating adjustments. In addition, the difference in means test indicates that soft rating adjustments reduce Type II errors to a greater extent for above-median EDF issuers than for below-median EDF issuers.

Relative to those in the non-defaulting-issuer sample, issuers in the defaulting-issuer sample are smaller (averaging assets of \$13.36 billion versus \$89.95 billion), have lower interest coverage (1.776 versus 8.243), have more debt (3.338 versus 1.694), more frequently have negative retained earnings (0.434 versus 0.191), and more likely have a credit enhancement feature (0.295 versus 0.122) and a redemption option (0.848 versus 0.561) on the debt issue. For the defaulting issuers' sample, high-EDF issuers have smaller asset values, lower interest coverage, more frequent large losses, smaller market values, and shorter issue maturities. For the non-defaulting-issuer sample, high-EDF issuers have higher debt-to-equity ratios, more frequent large losses, more frequent credit enhancement features, less frequent put options, and shorter maturities.

Before moving to our primary analyses, we examine descriptively whether soft rating adjustments grow in absolute value as default nears. In the first set of tests in Panel A of Table 2 using default issuers, we find that soft rating adjustments are on average higher in absolute value in the months leading up to default. Specifically, over the two-year period prior to default, ratings become over two notches higher ($F = 239.14$). In the second set of tests in Panel A using the non-default issuers, we provide descriptive information regarding how soft rating adjustments vary with the deciles of EDF. We measure EDF deciles during the year prior to the rating measurement. The visual pattern in $SoftAdj$, moving from the lowest decile of EDF to the highest, indicates that soft rating adjustments are higher in absolute value for the highest deciles. An F-test of the average difference in soft rating adjustments across the highest and lowest deciles of EDF is statistically significant at the 0.01 level ($F = 21.09$). This evidence suggests that soft rating adjustments are larger in absolute value for high-risk issuers.

In Panel B using the non-default issuers, we find that average EDF values grow substantially with Moody's actual rating, with lower actual ratings having higher average EDF values. We also find that average $SoftAdj$ values grow substantially with Moody's actual rating, with lower actual ratings being associated with larger soft adjustments in absolute value. Together, this evidence shows that our measure of default risk, EDF, is negatively associated with actual ratings and some evidence that Moody's makes larger (in absolute value) adjustments for issuers with higher assessed credit risk. As the soft adjustments are a component of the actual rating, the finding for soft adjustments, however, is somewhat mechanical.

3. Rating accuracy

In this section, we present our empirical analyses focusing on the accuracy of credit ratings. We examine how the Type I (e.g., missed default prediction) and Type II (e.g., false default prediction) rates attributable to soft rating adjustments vary with expected default risk. We also examine whether soft rating adjustments are more accurate at predicting default and recovery rates for issuers with higher expected default risk.

3.1. Do rating adjustments lower Type I errors for higher default risk issuers?

We begin by using the following logit regression to examine whether the credit rating agencies' use of discretion lowers the missed default predictions for issuers with higher default risk:

$$\begin{aligned} E_{TypeI} = {} & \vartheta_0 + \vartheta_1 EDF_{it} + \vartheta_2 PostCrisis_t + \vartheta_3 LMediaCov_{it} \\ & + \vartheta_4 EDF_{it} \times PostCrisis_t + \vartheta_5 EDF_{it} \times LMediaCov_{it} + \sum_j \vartheta_j X_{it} + u_{it} \end{aligned} \tag{1}$$

where E_{TypeI} is an indicator variable equal to one if agency ratings failed to predict an actual default event for a bond issue, and zero otherwise. We define a predicted default as a non-investment-grade rating.[9] Importantly, as our focus is on the effect of rating agencies' use of soft rating adjustments in the rating process, we need to remove from actual ratings the changing properties of ratings arising from improvements or declines in grid-based ratings. To accomplish this, we separately examine the incremental effect on Type I errors attributable to soft rating adjustments, $SoftAdjustAvoidE_{TypeI}$, versus the incidence of Type I errors based on grid-based ratings, $E_{TypeI,AdjustedGrid}$.

Our primary variable of interest, EDF, is measured one year prior to a default event and captures the ex ante likelihood of default a year prior to default. If high-risk issuers are of greater

[9] Our results are not sensitive to this definition of default prediction. We find similar results using both B1 and Caa1 as the cutoff rating levels for default prediction.

concern to rating agencies, then we expect a negative coefficient on EDF. Thus, the estimated coefficient on EDF for the specification of Equation (1) with $SoftAdjustAvoidE_{TypeI}$ as the dependent variable captures the extent to which soft rating adjustments improve rating accuracy and is our test of whether rating agencies use their discretion defensively for higher default risk issuers.

We also examine whether soft rating adjustments help further reduce Type I errors following the financial crisis and for more widely covered issuers. Similar to deHaan (2017) and Bonsall et al. (2018), respectively, we test the extent of the reduction in Type I errors following the financial crisis using the interacted variable $EDF \times PostCrisis$ and for more visible issuers using the interacted variable $EDF \times LMediaCov$. We include both interactions in the same regression model, as they capture distinct measures of when the rating agencies should face greater scrutiny from investors, regulators, and other market participants.

X is the set of control variables. Following Cheng and Neamtiu (2009), Bonsall (2014), and Bonsall et al. (2018) we control for issuer, issue, and macroeconomic differences in our tests using *LAsset*, *IntCov*, *DebtEquity*, *LargeLoss*, *NegRetain*, *Size*, *AssetBacked*, *Convertible, SeniorSecured*, *Enhance*, *Put*, *Redeem*, *Maturity*, *GDP*, *CRSPBond*, $S\&P500$, and $LDefaults$. Appendix A defines these and all other variables.[10]

Table 3 presents the results from estimating equation (1). Column (1) presents the results for our Type I error analysis using $SoftAdjustAvoidE_{TypeI}$ and column (2) presents the results for our Type I error analysis using $E_{TypeI,AdjustedGrid}$ as the dependent variables. The coefficient estimate for EDF in column (1) is statistically positive. This suggests that when we use soft rating adjustments to determine the occurrence of a Type I error rating agencies more accurately assess issuers' likelihood of default as the risk of default increases. By contrast, the coefficient estimate for EDF in column (2) is statistically insignificant. This evidence suggests that rating agencies use their discretion defensively for higher risk issuers and that such discretion results in more accurate ratings in advance of actual default. In terms of magnitude, using partial effects, soft rating adjustments avoid a Type I error in actual ratings at a rate that is 8.1 percentage points higher for issuers at the third quartile value of EDF compared with that for issuers at the first

[10] In the Type I and Type II analyses, for comparability, we follow prior related research by including macroeconomic variables (i.e., GDP, $CRSPBond$, $S\&P500$, and $LDefaults$) rather than including year fixed effects to control for changing macroeconomic conditions.

quartile value of EDF.[11] This difference in the error avoidance rate for soft rating adjustments is approximately 38.3 percent of the overall soft rating adjustment Type I error avoidance rate of 21.1 percent for issuers at the median value of EDF.

We also observe a significantly positive estimate for $EDF \times PostCrisis$ when we use soft rating adjustments as the basis for determining the occurrence of a Type I error. Conversely, we detect no statistically significant estimate for $EDF \times PostCrisis$ when we use grid-based ratings to determine the occurrence of a Type I error. These results provide evidence that rating agencies use their discretion even more defensively for higher default risk issuers after the financial crisis, leading to even more accurate ratings prior to events of default. The estimate for $EDF \times PostCrisis$ in column (1) of Table 3 suggests an economically significant impact of this use of discretion. In the post-financial crisis period, the soft adjustment Type I error avoidance rate for issuers at the third quartile value of EDF is 12.1 percentage points higher than that for issuers at the first quartile value of EDF in the pre-financial crisis period—a 57.3 percent decrease relative to the overall Type I error avoidance rate in the sample. We find similar evidence for $EDF \times LMediaCov$ for soft rating adjustments relative to grid-based ratings. This evidence suggests that the rating agencies also use their discretion to a greater extent for more visible issuers. The Type I error avoidance rate from soft adjustments at the third quartile value of both EDF and $LMediaCov$ is 15.4 percentage points higher than that for issuers at the first quartile value of both EDF and $LMediaCov$—a 72.6 percent decrease.

3.2. Do rating adjustments lower Type II errors for higher default risk issuers?

We next examine whether false default predictions are lower for issuers with higher expected default risk. In addition, we examine whether the negative relationship is more pronounced following the financial crisis and for issuers with greater media coverage. We investigate these issues using the following logit regression model:

[11] In the Type I and Type II analyses that estimate logit regression models, we follow the suggestions of Greene (2010) and report coefficient estimates in the tables for hypothesis testing. In addition, we report the partial effects for the interacted variables for descriptive purposes, as partial effects are difficult to meaningfully evaluate.

$$
\begin{aligned}
E_{TypeII} = {} & \chi_0 + \chi_1 EDF_{it} + \chi_2 PostCrisis_t + \chi_3 LMediaCov_{it} \\
& + \chi_4 EDF_{it} \times PostCrisis_t + \chi_5 EDF_{it} \times LMediaCov_{it} + \sum_j \chi_j X_{it} + \omega_{it}
\end{aligned} \tag{2}
$$

where E_{TypeII} is an indicator variable equal to one if agency ratings predict a default event for a bond issue where one does not eventually occur, and zero otherwise. For purposes of measuring E_{TypeII}, we define a predicted default as a non-investment-grade rating.[12] Again, we separately examine the frequency of Type II errors using soft rating adjustments, $SoftAdjustAvoidE_{TypeII}$, and grid-based ratings, $E_{TypeII,AdjustedGrid}$. If the accuracy of ratings for issuers with higher levels of EDF are of relatively greater concern to rating agencies, then Type II error rates should be lower. We measure EDF one year before a non-default event. The estimated coefficient on EDF in the specification of Equation (2) with soft adjustments as the dependent variable captures rating agencies' discretion over the improvement in ratings through soft rating adjustments. If discretion over soft rating adjustments is used strategically to achieve more accurate non-default predictions, the EDF coefficient for the $SoftAdjustAvoidE_{TypeII}$ estimation is expected to be positive. If rating agencies have greater reputational concerns following the financial crisis and for more visible issuers, then the coefficients for $EDF \times PostCrisis$ and $EDF \times LMediaCov$ should be positive when $SoftAdjustAvoidE_{TypeII}$ is the dependent variable. The control variables (X) in Equation (2) are similar to those used in prior research examining Type II error rates (e.g., Cheng and Neamtiu, 2009; Bonsall, 2014; Bonsall et al., 2018): *LAsset*, *IntCov*, *DebtEquity*, *LargeLoss*, *NegRetain*, *Size*, *SeniorSecured*, *Enhance*, *Put*, *Redeem*, *Maturity*, *GDP*, *CRSPBond*, *S&P*500, and *LDefaults*.[13]

Table 4 reports the results from our estimation of Equation (2). Column (1) of Table 4 presents the results for our Type II error analysis using soft rating adjustments, while column (2) presents the results for our Type II error analysis using grid-based ratings. In column (1), the coefficient estimate for EDF is statistically positive, suggesting that rating agencies use soft rating adjustments strategically to improve rating accuracy for issuers with higher expected default risk. In contrast, the coefficient estimate for EDF in column (2) is statistically positive, consistent with ratings based on financial ratios falsely predicting default to a greater extent when issuer default risk is higher.

[12] Our results are not sensitive to this definition of default prediction. We find similar results using both B1 and Caa1 as the cutoff rating levels for default prediction.

[13] While prior research includes *AssetBacked* and *Convertible* variables, they are excluded from our analyses as no issuances in our sample are asset backed or contain a convertibility option.

The estimated coefficient on EDF in column (2) is consistent with an 81 basis point increase in the Type II error rate across third quartile and first quartile EDF issuers—an approximately 3.1 percent increase relative to the 25.9 percent Type II error rate at the median level of EDF. In column (1) of Table 4, the coefficient on EDF is consistent with a soft adjustment Type II error avoidance rate that is 71 basis points higher for issuers at the third quartile of EDF compared to issuers at the first quartile of EDF; this absolute magnitude is consistent with a relative increase in the Type II error avoidance rate from soft adjustments of 9.5 percent based on the value of $SoftAdjustAvoidE_{TypeII}$ at the median value of EDF. Overall, rating agencies appear to use their discretion over soft rating adjustments for higher default risk issuers to offset the increase in default prediction errors based on financial ratios.

Turning to the interaction term $EDF \times PostCrisis$, we find a significantly positive coefficient in column (1) but fail to find a statistically significant coefficient in column (2). The findings in column (1) are consistent with soft rating adjustments for higher default risk issuers leading to relatively fewer Type II errors in the post-financial crisis period, providing further evidence that rating agencies improve the accuracy of their ratings for higher default risk issuers through soft rating adjustments. This evidence suggests greater ongoing monitoring of these issuers, which represent a potentially costlier reputational threat in the case of an ex post misclassified rating. Conversely, the absence of statistically significant results in column (2) for grid-based ratings are suggestive of no change in financial ratios' accuracy following these shocks. Regarding the interaction term $EDF \times LMediaCov$, we also find a statistically significant positive coefficient in column (1) but fail to find a statistically significant coefficient in column (2). The evidence suggests that greater reputational concerns for highly visible issuers lead the rating agencies to use soft rating adjustments to reduce Type II errors for issuers with greater media coverage.

Combined, the findings in Table 4 indicate that the accuracy of grid-based ratings declines with an issuer's EDF (i.e., rating agencies overestimate default risk for higher default risk issuers), but that rating agencies' use of discretion through soft adjustments offsets this reduction in accuracy.[14] More importantly, the offset in the reduction in accuracy from the use of discretion is more

[14]The possibility exists that grid-based rating models tend to underestimate default risk for high risk issuers and require more soft adjustments to make up for the underestimation, consistent with the univariate evidence in Table 2 that soft adjustments are larger in absolute value for higher default risk issuers. Inconsistent with this possibility, the evidence that EDF is significantly positively associated with Type II error rates when using grid-based ratings in Table 4 indicates that default risk models actually tend to overestimate default risk for high default risk issuers.

pronounced for higher default risk issuers when rating agencies should be trying to rebuild their reputations and limiting possible increased investor monitoring, regulatory oversight and legal liability, and for issuers that pose greater reputational risk—due to their greater visibility—if a rating failure occurs.

3.3. Do soft rating adjustments better predict default for higher default risk issuers?

The improvements in ratings for issuers with greater default risk could lead to ratings that are more predictive of actual defaults. We investigate the predictive ability of ratings for future defaults with the following logit regression model:

$$
\begin{aligned}
Default_{it+k} = {} & \beta_0 + \beta_1 EDF_{it} + \beta_2 SoftAdj_{it} + \beta_3 QuantRating_{Adj_{it}} + \beta_4 EDF_{it} \times SoftAdj_{it} \\
& + \beta_5 EDF_{it} \times QuantRatingAdj_{it} + \beta_6 PostCrisis_t + \beta_7 LMediaCov_{it} \\
& + \beta_8 EDF_{it} \times PostCrisis_t + \beta_9 EDF_{it} \times LMediaCov_{it} \\
& + \beta_{10} SoftAdj_{it} \times PostCrisis_t + \beta_{11} SoftAdj_{it} \times LMediaCov_{it} \\
& + \beta_{12} QuantRatingAdj_{it} \times PostCrisis_t + \beta_{13} QuantRatingAdj_{it} \times LMediaCov_{it} \\
& + \beta_{14} EDF_{it} \times SoftAdj_{it} \times PostCrisis_t + \beta_{15} EDF_{it} \times SoftAdj_{it} \times LMediaCov_{it} \\
& + \beta_{16} EDF_{it} \times QuantRatingAdj_{it} \times PostCrisis_t \\
& + \beta_{17} EDF_{it} \times QuantRatingAdj_{it} \times LMediaCov_{it} + \sum_j \beta_j X_{it} + u_{it}
\end{aligned} \tag{3}
$$

where $Default_{t+k}$ is a binary variable equal to one if an issuer defaults alternatively over the one- or three-year period after period t, and zero otherwise. We expect that both soft rating adjustments and grid-based ratings are predictive of future default events and, therefore, expect the coefficients on $SoftAdj$ and $QuantRating_{Adj}$ to be negative. Further, our primary prediction is that the discretionary soft rating adjustments are more predictive of future defaults for issuers with higher default risk, again measured using EDF. This leads to the expectation that the coefficient on the interaction $SoftAdj \times EDF$ is negative. We include the interaction $EDF \times QuantRating_{Adj}$ but do not make a directional prediction. To provide evidence of whether the post-financial crisis period led to more defensive behavior by the rating agencies, we also include the three-way interaction of

We also fail to find that $EDF \times PostCrisis$ or $EDF \times LMediaCov$ are significantly positively associated with Type II error rates for grid-based ratings in Table 4. In addition, we fail to find that EDF, $EDF \times PostCrisis$, or $EDF \times LMediaCov$ are significantly associated with Type I error rates for grid-based ratings in Table 3, or that, as discussed later, $EDF \times QuantRatingAdj$, $EDF \times QuantRatingAdj \times PostCrisis$, or $EDF \times QuantRatingAdj \times LMediaCov$ are significantly associated with predicting issuer default or with predicting default recovery losses in Tables 5 and 6, respectively. Together, these findings either provide evidence inconsistent with or fail to support this alternative explanation.

$EDF \times SoftAdj \times PostCrisis$, which we also predict to be negative if rating agencies use their discretion even more defensively for higher default risk issuers during the post-financial crisis period. To provide evidence of whether more visible issuers lead to greater strategic behavior by the rating agencies, we similarly include the three-way interaction of $EDF \times SoftAdj \times LMediaCov$, which we also predict to be negative. We allow for similar interactions with $EDF \times QuantRating_{Adj}$ but do not make directional predictions.

While not the main focus of our analysis, if the post-financial crisis period and more widely covered issuers have ratings with greater default predictive value, then we also expect negative coefficients for $SoftAdjust \times PostCrisis$ and $SoftAdjust \times LMediaCov$. To control for various issuer characteristics on default probabilities, following Becker and Milbourn (2011), we include several control variables (X): $LSales$, $LAsset$, $Cash/Assets$, $(Cash/Assets)^2$, $EBITDA/Sales$, $(EBITDA/Sales)^2$, $OperCF/Sales$, $(OperCF/Sales)^2$, $IntExp/EBITDA$, $(IntExp/EBITDA)^2$, $Debt/Assets$, and $(Debt/Assets)^2$.

Table 5 presents the results from our test of the effect of issuer credit risk on credit ratings' default prediction. For both default horizons, consistent with both grid-based ratings and soft rating adjustments being predictive of future defaults, we observe significantly negative coefficient estimates for $SoftAdj$ and $QuantRating_{Adj}$. We also find a significantly negative coefficient estimate for $EDF \times SoftAdj$, suggesting that rating agencies' defensive use of their discretion leads to ratings that are more predictive of future default for issuers with higher credit risk. For our tests of the post-financial crisis period and for more widely covered issuers, we observe significantly negative coefficient estimates for $EDF \times SoftAdjust \times PostCrisis$ and $EDF \times SoftAdjust \times LMediaCov$. These results reinforce our inference that soft rating adjustments become more predictive of future default for higher default risk issuers. In contrast, the corresponding coefficient estimates that use $QuantRating_{Adj}$, instead of $SoftAdj$, are insignificant and are statistically different from their $SoftAdj$ counterparts ($t - statistic = -2.46$, $t - statistic = -2.28$, and $t - statistic = -1.84$, respectively, for the interactions with EDF, EDF and $PostCrisis$, and EDF and $LMediaCov$ using the $t + 1$ horizon). This reinforces our inference that soft rating adjustments are used strategically by credit rating agencies. Overall, the findings in Table 5 support our prediction that ratings become more accurate for higher default risk issuers based on the attribute of rating default predictive value.

3.4. *Do soft ratings better predict default recovery losses for higher default risk issuers?*

Given the observed improvements in the predictive accuracy of ratings for higher default risk issuers prior to default, we next provide evidence on whether these properties lead to ratings that are more relevant for predicting default recoveries. Borrowers are fundamentally interested in the likelihood of default and potential losses given default. Moody's ratings capture both aspects of default risk. We examine the default recovery rates for specific types of default, as identified by Moody's DRD: Chapter 11 liquidation and restructuring, distressed exchanges, and payment defaults.[15] For each event, we examine whether rating discretion predicts creditor recovery rates. Similar to Jankowitsch, Nagler, and Subrahmanyam (2014), we examine recovery rates for default events using the following OLS regression model:

$$\begin{aligned} DefaultPrice_{it} = {} & \delta_0 + \delta_1 EDF_{it} + \delta_2 SoftAdj_{it} + \delta_3 QuantRating_{Adj_{it}} + \delta_4 EDF_{it} \times SoftAdj_{it} \\ & + \delta_5 EDF_{it} \times QuantRating_{Adj_{it}} + \delta_6 PostCrisis_t + \delta_7 LMediaCov_{it} \\ & + \delta_8 EDF_{it} \times PostCrisis_t + \delta_9 EDF_{it} \times LMediaCov_{it} \\ & + \delta_{10} SoftAdj_{it} \times PostCrisis_t + \delta_{11} SoftAdj_{it} \times LMediaCov_{it} \\ & + \delta_{12} QuantRating_{Adj_{it}} \times PostCrisis_t + \delta_{13} QuantRating_{Adj_{it}} \times LMediaCov_{it} \\ & + \delta_{14} EDF_{it} \times SoftAdj_{it} \times PostCrisis_t + \delta_{15} EDF_{it} \times SoftAdj_{it} \times LMediaCov_{it} \\ & + \delta_{16} EDF_{it} \times QuantRating_{Adj_{it}} \times PostCrisis_t \\ & + \delta_{17} EDF_{it} \times QuantRating_{Adj_{it}} \times LMediaCov_{it} + \sum_j \delta_j X_{it} + a_k + \alpha_t + \varepsilon_{it} \quad (4) \end{aligned}$$

where $DefaultPrice$ is defined as the default price, measured as the trading price of defaulted debt, expressed as a percentage of par, as of the default date for distressed exchanges, or 30 days after default for all other types of default. If rating agencies' use of discretion is informative about loss recovery prior to default, we expect a positive coefficient on $SoftAdj$. We also expect that grid-based ratings are associated with higher recovery rates and, accordingly, a positive coefficient on $QuantRating_{Adj}$. Moreover, we expect that discretion over ratings is relatively more informative for issuers with greater default risk and, thus, we predict that the coefficient on the interaction $EDF \times SoftAdj$ is positive. We include the interaction $EDF \times QuantRating_{Adj}$ but do not make a directional prediction. In addition, we predict that rating agencies will use their discretion over soft rating adjustments defensively for higher default

[15] Because the types of default events are all-inclusive, we exclude an indicator variable for missed payments in our regressions.

risk issuers to a greater extent following the financial crisis and for issuers with greater media coverage. Accordingly, we predict positive coefficients on the triple interactions $EDF \times SoftAdj \times PostCrisis$ and $EDF \times SoftAdj \times LMediaCov$. We also create similar interactions with $EDF \times QuantRating_{Adj}$ but do not make directional predictions. X is the set of control variables similar to those used in Jankowitsch et al. (2014) that includes factors for bond, default type, and issuer characteristics: $Coupon$, $SeniorSecured$, $Subordinated$, $DistressedExchange$, $Chapter11$, $Equity$, $DefaultBarrier$, $LTDIssuance$, $Profitability$, $Intangibility$, $Receivables$, $LAsset$, and $LEmployees$. We also include industry (α_k) and year (α_t) fixed effects to control for differences in industry-specific default risk and market-wide default risk, following Jankowitsch et al. (2014).

Table 6 presents the results from estimating Equation (4). Column (1) uses credit rating information at year $t-1$ relative to default and column (2) uses credit rating information at year $t-2$. In both columns, the coefficient estimates on $SoftAdj$ are statistically positive, consistent with more favorable discretion over soft rating adjustments predicting higher lender recoveries in bankruptcy. We also find that the coefficients on $QuantRating_{Adj}$ are statistically positive, consistent with grid-based credit ratings providing incremental information about future recoveries from defaulting issuers. In addition, we find that the coefficient on the interaction $EDF \times SoftAdj$ is statistically positive. This finding suggests that rating discretion using soft adjustments has greater correspondence with the eventual default recovery rates for issuers with greater potential default risk.[16] Further, we find evidence that the coefficients on $EDF \times SoftAdj \times PostCrisis$ and $EDF \times SoftAdj \times LMediaCov$ are statistically positive, consistent with rating agencies using their discretion defensively to a greater extent for higher default risk issuers in the post-financial crisis period and those with greater media coverage. In contrast, the corresponding coefficient estimates that use $QuantRating_{Adj}$, instead of $SoftAdj$, are insignificant and are statistically different from their $SoftAdj$ counterparts ($t-statistic = 1.87$, $t-statistic = 2.60$, and $t-statistic = 1.97$, respectively for the interactions with EDF, EDF and $PostCrisis$, and EDF and $LMediaCov$).

[16]These findings allow for somewhat different inferences from the Type I error rate findings. Moody's states that its expected loss approach to ratings "address the probability that a financial obligation will not be honored as promised (i.e., probability of default, or "PD"), and any financial loss suffered in the event of default" (Securities and Exchange Commission, 2012, p. 21). Accordingly, Moody's ratings reflect the issuer's potential credit loss, which is the probability of default multiplied by the loss given default. The Type I error analysis provides evidence of when the accuracy of soft rating adjustments better predicts default events. By contrast, the default recovery loss analysis provides evidence of when soft rating adjustments better predict actual credit losses.

4. Ratings relevance

This section examines whether soft rating adjustments are more relevant for issuers with higher expected default risk. We investigate the relevance of ratings in two important settings. First, we investigate whether soft rating adjustments better explain initial offering yields for higher default risk issuers. Second, we examine whether the market reaction to soft rating adjustment changes is larger for higher default risk issuers.

4.1. Initial offering yields

We begin by examining whether ratings for issuers that have higher expected default risk better reflect the information in offering yield spreads for corporate bonds. We use the following OLS regression specification:

$$\begin{aligned}
YSpread = {} & \varsigma_0 + \varsigma_1 EDF_{it} + \varsigma_2 SoftAdj_{it} + \varsigma_3 QuantRating_{Adj_{it}} + \varsigma_4 EDF_{it} \times SoftAdj_{it} \\
& + \varsigma_5 EDF_{it} \times QuantRating_{Adj_{it}} + \varsigma_6 PostCrisis_t + \varsigma_7 LMediaCov_{it} \\
& + \varsigma_8 EDF_{it} \times PostCrisis_t + \varsigma_9 EDF_{it} \times LMediaCov_{it} + \varsigma_{10} QuantRating_{Adj_{it}} \times PostCrisis_t \\
& + \varsigma_{11} SoftAdj_{it} \times PostCrisis_t + \varsigma_{12} SoftAdj_{it} \times LMediaCov_{it} \\
& + \varsigma_{13} QuantRating_{Adj_{it}} \times PostCrisis_t + \varsigma_{14} QuantRating_{Adj_{it}} \times LMediaCov_{it} \\
& + \varsigma_{15} EDF_{it} \times SoftAdj_{it} \times PostCrisis_t + \varsigma_{16} EDF_{it} \times SoftAdj_{it} \times LMediaCov_{it} \\
& + \varsigma_{17} EDF_{it} \times QuantRating_{Adj_{it}} \times PostCrisis_t \\
& + \varsigma_{18} EDF_{it} \times QuantRating_{Adj_{it}} \times LMediaCov_{it} + \sum_j \varsigma_j X_{it} + \alpha_t + u_{it} \qquad (5)
\end{aligned}$$

where $YSpread$ is the initial offering yield spread on a newly issued bond. Issuers with higher soft rating adjustments and grid-based quantitative ratings should have lower yield spreads. This leads to the prediction of negative coefficients for $SoftAdj$ and $QuantRating_{Adj}$. Moreover, for issuers with higher expected default risk, we expect that soft rating adjustments should be even more informative due their greater incorporation of private information and, thus, predict a negative coefficient for $EDF \times SoftAdjust$. In addition, we expect that the post-financial crisis period resulted in credit rating agencies increasing the informativeness of soft rating adjustments to rebuild their reputations and, thus, predict a negative coefficient for $EDF \times SoftAdj \times PostCrisis$. We also expect that more widely followed issuers will lead to greater reputational concerns for the rating agencies and, thus, predict a negative coefficient for $EDF \times SoftAdj \times LMediaCov$. X is a set of control variables following Beaver et al. (2006) that includes various issuer and issue characteristics: Lev, $IntCov$, $ProfitMargin$, $LAsset$, $LIssueAmt$, $Maturity$, $Senior$, and $Secured$. Following Beaver et al. (2006), we also include year (α_t) fixed effects to control for changing market interest rates across time.

Table 7 presents the results from our test in the setting of corporate bond offering yield spreads. Consistent with both grid-based ratings and soft rating adjustments being informative to bond investors about credit risk, we obtain significantly negative estimates for the coefficients on $SoftAdj$ and $QuantRating_{Adj}$. We also find a significantly negative estimate for the coefficient $EDF \times SoftAdjust$, which suggests that rating agencies' defensive use of their discretion leads to ratings that are more informative to bond investors for issuers with higher credit risk. These results reinforce our inference that ratings become more informative to bond investors for higher default risk issuers. Further, we obtain significantly negative estimates for the coefficients on $EDF \times SoftAdj \times PostCrisis$ and $EDF \times SoftAdj \times LMediaCov$. These results indicate that ratings become overall more informative as a result of the rating agencies' efforts to rebuild their reputations after the financial crisis and when the visibility of the issuer poses a greater reputational threat to rating agencies in the event of a rating failure. We fail to find similar significant evidence for the interactions with $QuantRating_{Adj}$. Overall, the evidence in Table 7 supports our prediction that rating agencies strategically use soft rating adjustments to make ratings more relevant for higher default risk issuers.

4.2. Equity market reaction to rating adjustment changes

We next investigate whether the market reaction to soft rating adjustment changes is larger for higher default risk issuers. First, following Beaver et al. (2006), we examine if returns reflect upgrades and downgrade decisions attributable to soft adjustments and quantitative ratings in the days and months prior to the decisions. We focus on three return windows: $CAR_{-11,-1}$, $CAR_{-120,-1}$, and $CAR_{-240,-1}$. We present the results in Panel A of Table 8. For rating downgrades, we find evidence that returns reflect the downgrade decision attributable to soft adjustment and quantitative rating changes in the months leading up to the decision, but that the market incorporates less information in soft adjustment downgrades prior to the announcement: cumulative abnormal returns (CARs) are smaller in magnitude for soft adjustment downgrades of -0.097 than for quantitative rating downgrades of -0.227. In addition, we find that the proportion of the total CAR, including the rating change announcement period, impounded before the rating change is smaller for soft adjustment downgrades than for quantitative rating downgrades. On average, soft adjustment downgrades experience a total CAR from day -240 to day +1 of -18.3 percent while quantitative rating downgrades experience an average CAR over the same period of -23.4 percent (untabulated). Thus, only 53 percent ($\frac{-0.097}{-0.183}$) of the total CAR precedes soft adjustment downgrades, whereas 97 percent ($\frac{-0.227}{-0.234}$) of the total CAR precedes quantitative rating downgrades. This suggests that soft rating adjustment changes contain more private information than quantitative rating changes. For rating upgrades, we find that returns reflect the upgrade decision attributable to soft adjustment and quantitative rating changes in the months leading up to the decision, but fail to find a difference in the market's ability to incorporate information about soft adjustment versus quantitative upgrades prior to the announcement. Descriptively, 78 percent ($\frac{0.162}{0.209}$) of the total CAR precedes soft adjustment upgrades and 96 percent ($\frac{0.184}{0.191}$) precedes quantitative rating upgrades (untabulated). This evidence is consistent with rating agencies being more sluggish to use their private information to upgrade issuers using soft adjustments.

Second, we examine if the market reacts to soft adjustment changes when they are announced. Evidence of a larger reaction for issuers with higher default risk would be consistent with greater monitoring efforts by rating agencies for this group of debt issuers. Using the following OLS regression model, we examine soft rating adjustments separately for those that lead to rating downgrades and upgrades:

$$\begin{aligned}
CAR_{it} = {} & \varphi_0 + \varphi_1 SoftAdjIndicator_{it} + \varphi_2 EDF_{it} \\
& + \varphi_3 SoftAdjIndicator_{it} \times EDF_{it} + \varphi_4 PostCrisis + \varphi_5 LMediaCov_{it} \\
& + \varphi_6 SoftAdjIndicator_{it} \times PostCrisis_t + \varphi_7 SoftAdjIndicator_{it} \times LMediaCov_{it} \\
& + \varphi_8 EDF_{it} \times PostCrisis_t + \varphi_9 EDF_{it} \times LMediaCov_{it} \\
& + \varphi_{10} SoftAdjIndicator_{it} \times EDF_{it} \times PostCrisis_t \\
& + \varphi_{11} SoftAdjIndicator_{it} \times EDF_{it} \times LMediaCov_{it} \\
& + \varphi_{12} RChange_{it} + \varphi_{13} IGrade_{it} + \varphi_{14} Days_{it} + \tau_{it}
\end{aligned} \tag{6}$$

where CAR is the cumulative abnormal three-day return centered on the date of a rating change (i.e., upgrade or downgrade), following Jorion et al. (2005). Our primary variable of interest is

$SoftAdjIndicator$, an indicator variable equal to one if an issuer's rating change is driven solely by a change in an issuer's soft rating adjustment, and zero otherwise. We expect that downgrades and upgrades driven only by changes in soft rating adjustments should lead to incrementally negative and positive market reactions, respectively. In addition, we expect the market reaction to be more pronounced when issuer default risk is higher, as measured by EDF. Together, this leads to negative (positive) coefficients for $SoftAdjIndicator$ and $SoftAdjIndicator \times EDF$ for rating downgrades (upgrades). We also predict that the incentives faced by the credit rating agencies in the post-financial crisis period and for widely followed issuers yield coefficients for $SoftAdjIndicator \times EDF \times PostCrisis$ and $SoftAdjIndicator \times EDF \times LMediaCov$ that are negative (positive) for downgrades (upgrades). Our controls from Jorion et al. (2005) take into account the magnitude of rating changes, $RChange$, (where the constant term reflects rating changes of one notch), revisions across the important investment-/speculative-grade threshold ($IGrade$), and the length of time between rating revisions ($Days$).

Panel B of Table 8 presents our findings from estimating Equation (6). Column (1) presents the results for rating downgrades, while column (2) presents the results for rating upgrades. In column (1), the coefficient estimate on $SoftAdjIndicator$ is statistically negative, suggesting that downgrades driven solely by changes in soft rating adjustments lead to an incrementally negative equity market reaction. The estimated coefficient on $SoftAdjIndicator \times EDF$ is also statistically negative, consistent with downgrades that are driven solely by rating agencies' discretion over soft adjustments leading to even greater revisions by the market for issuers with higher default risk. In addition, we find statistically negative coefficient estimates for $SoftAdjIndicator \times EDF \times PostCrisis$ and $SoftAdjIndicator \times EDF \times LMediaCov$, consistent with rating agencies using their discretion even more defensively for higher default risk issuers following the financial crisis and for higher visibility issuers, and the equity market responding to downgrades accordingly. Rating downgrades are also explained by $Days$.

Column (2) of Table 8 shows positive and significant estimates for $SoftAdjIndicator$ and $SoftAdjIndicator \times EDF$, consistent with the equity market responding more to upgrades driven solely by rating agencies' discretion and incrementally so for issuers with higher default risk. For our test examining the post-financial crisis period and more visible issuers, we fail to find evidence of the rating agencies using their discretion more defensively for higher default risk issuers for upgrades. This lack of evidence is consistent with prior research on the equity market response to credit rating changes, which has shown a much more limited reaction to rating upgrades (e.g., Holthausen and Leftwich, 1986; Jorion et al., 2005). Taken together, while we find that investors are able to anticipate some of the information in soft rating changes prior to their release, our findings also indicate that such adjustments for rating downgrades are more timely for issuers with higher expected default risk.

5. Rating committee organization for high default issuers

Our last analysis investigates a potential mechanism through which the rating agencies achieve more accurate and relevant ratings for higher default risk issuers. Moody's states that ratings are initially set and later changed through rating committees, which are steered by lead analysts and include a managing director and sometimes other analysts (Moody's Investors Service, 2009). As Moody's discusses, "the committee may be expanded to include as many perspectives and disciplines needed to address all analytical issues relevant to the issuer and the security being rated" (Moody's Investors Service, 2009, p. 1). Consistent with rating agencies strategically assigning better analysts to issuers that pose greater reputational risk, using data from Fracassi et al. (2016),[17] Bonsall et al. (2018) find that issuers with greater media coverage are assigned analysts that are better educated and more experienced. The evidence is consistent with conversations by the authors with current and former senior-level employees that better analysts are assigned to more visible issuers.

Moody's may through similar means achieve more accurate and relevant ratings for higher default risk issuers by assigning better analysts. Consistent with the approach used by Fracassi et al. (2016) and Bonsall et al. (2018), we investigate if the rating agencies strategically assign better educated and more experienced credit rating analysts using the following attributes of assigned analysts: MBA, $Top\ 5\ MBA$, $Non\ Top\ 5\ MBA$, $Female$, $Analyst\ Age$, $Analyst\ Tenure: Firm$, $Analyst\ Tenure: Industry$, $Analyst\ Tenure: Agency$, and $\#\ Firms\ Covered$. We predict that issuers with higher EDFs will be assigned analysts that are better educated (i.e., those with MBAs, especially from top programs), female, older, have more industry and agency experience, and greater firm coverage. We do not make a prediction regarding an analyst's tenure with the firm,

[17]Fracassi et al. (2016) collect the names of credit analysts from rating reports and match the names of the analysts with hand-collected demographic data from LinkedIn profiles and other web sources.

$Analyst\ Tenure:\ Firm$, as greater tenure can provide analysts with greater private information regarding the issuer's creditworthiness but can alternatively lead to tight relationships with and loyalty to the issuer's managers. In addition, we include $LMediaCover$ to control for the influence of an issuer's visibility on the assignment of analysts and $LAsset$, $IntCov$, $DebtEquity$, $LargeLoss$, $NegRetain$, GDP, $CRSPBond$, $S\&P500$, and $LDefaults$ to capture other important attributes of the issuer and general economic and market conditions.

Table 9 provides the logit and OLS regression coefficients for the different estimations of the relation between an issuer's expected default risk and the quality of assigned credit analysts.[18] In the first three columns, the coefficient estimates for EDF are all statistically positive in the MBA, $Top\ 5\ MBA$, and $Non\ Top\ 5\ MBA$ logit regression models, with the coefficient for $Top\ 5\ MBA$ being greater than for $Non\ Top\ 5\ MBA$. The partial effects are relatively large; for instance, an interquartile range increase in EDF results in a 14 percent increase in an analyst holding an MBA being assigned. This evidence is consistent with rating agencies assigning better educated analysts to issuers with higher expected default risk. In columns (4) and (5), we also find that the coefficient estimates for EDF are statistically positive for the $Female$ and $Analyst\ Age$ regressions, suggesting that female analysts, which typically self-select into the profession if they are superior forecasters because of perceived discrimination in the analyst market (Kumar, 2010), and more experienced analysts are more likely to be assigned to issuers with higher expected default risk. In column (6), we find a significantly negative EDF coefficient in the $Analyst\ Tenure:\ Firm$ estimation, consistent with more experienced analysts being viewed as having a conflict of interest and being less likely to be assigned to issuers with higher expected default risk. In the last three columns, the coefficients for EDF are all statistically positive in the $Analyst\ Tenure:\ Industry$, $Analyst\ Tenure:\ Agency$, and $\#\ Firms\ Covered$ estimations. Similar to the interpretations by Fracassi et al. (2016), these findings provide further evidence that more experienced or skilled credit analysts are more likely to be assigned to issuers with higher expected default risk.[19] For the control variables, we find consistent evidence that better educated and more experienced analysts

[18] As before, for the logit regression models, we follow the recommendations of Greene (2010) and use coefficient estimates for hypothesis testing and discuss partial effects for descriptive purposes.

[19] Our interpretation of $\#\ Firms\ Covered$ being associated with the skill of the credit analyst follows from Fracassi et al. (2016)'s findings that analysts covering more firms are less biased and more accurate. Unlike individual financial analysts that become busy and less attentive when they cover more firms, credit rating teams can grow in size to accommodate a more skilled credit analyst that would otherwise become too busy from covering more firms.

are more likely to be paired with a widely covered issuer and some evidence that more experienced analysts are more likely to be matched with a large issuer.

6. Conclusion

Credit rating agencies have faced considerable criticism following rating failures in the early 2000s (e.g., Enron and WorldCom) and more recently with the 2008 financial crisis. Critics of major rating agencies suggest that conflicts of interest inherent to the issuer-pay compensation model and excessive regulatory reliance on ratings lead to inflated and untimely credit risk assessments of both issuers and securities. Rating agencies, in contrast, argue that their reputations are their most important assets and the threat of possible reputational harm from issuing low quality ratings offsets incentives to cater to clients.

This study examines whether major credit rating agencies use their discretion defensively for higher expected default risk issuers, leading to more accurate and relevant ratings for these riskier issuers. Our examination is motivated by arguments in Bolton et al. (2012) that investors will punish rating agencies for falsely reporting issuer default risk prior to default. Because investors typically can only detect rating failures at default and rating agencies are assumed to possess private information, rating agencies face an incentive to issue higher quality ratings for higher expected default risk issuers. Rating failures by high-risk issuers can lead to economic harm arising from investors relying less on the agency's ratings (deHaan, 2017), agencies receiving a lower share of the new issuances rating market (Bonsall et al., 2018), lower regulatory reliance on ratings, and increased regulatory oversight and legal liability.

We examine this question by looking at qualitative soft rating adjustments, which are subject to the greatest discretion by rating committees; grid-based ratings, in contrast, are based on a weighted average of GAAP based financial ratios adjusted for standard hard adjustments for items such as off-balance sheet amounts. Consistent with our predictions, we find that soft rating adjustments lead to more accurate ratings. Specifically, we find that both missed default predictions and false default predictions are less frequent for issuers with higher pre-default credit risk. In addition, we find that soft rating adjustments better predict future default and future default recovery rates for issuers with higher expected default risk. Further, we find that qualitative soft rating adjustments lead to more relevant ratings. That is, we find that the mapping between ratings and initial offering yield spreads is higher for issuers with higher expected default risk and that equity market reactions to rating downgrades for such issuers are higher, with improvements being attributable to soft rating adjustments. Our findings of greater accuracy and relevance are more pronounced in the post-financial crisis period—a period when the rating agencies were trying to rebuild their reputations—and for more visible issuers—issuers posing a greater reputational risk for rating agencies if a rating failure occurs. Finally, we find that the rating agencies strategically assign better analysts (e.g., analysts holding MBAs, with more experience, and covering more issuers) to higher-risk issuers, indicating one channel through which the rating agencies can achieve more accurate and relevant ratings for higher-risk issuers.

Overall, our findings offer important new insights to the credit rating literature. Specifically, our findings confirm the theoretical predications of Bolton et al. (2012), indicating that rating agencies are more defensive for higher expected default risk issuers due to economic harm from rating failures. In addition, our findings indicate that rating agencies assign ratings defensively across rating levels for issuers with higher ex ante default risk. This evidence is in sharp contrast to that of prior research findings of client catering at important thresholds (e.g., rating agencies being reluctant to assign ratings below the investment-grade threshold). Further, our findings contribute to recent research examining the extent of ongoing monitoring by the rating agencies. Unlike prior research that finds only limited monitoring after issuance, our findings indicate that soft rating adjustments are updated more frequently and are more reflective of agencies' private information for higher-risk issuers.

References

Alp, A. (2013). "Structural shifts in credit rating standards". *The Journal of Finance* 68.6, pp. 2435–2470.

Baghai, R. and B. Becker (2020). "Reputations and credit ratings: Evidence from commerical mortgage-backed securities". *Journal of Financial Economics* 135.2, pp. 425–444.

Baghai, R. P. and B. Becker (2018). "Non-rating revenue and conflicts of interest". *Journal of Financial Economics* 127.1, pp. 94–112.

Baghai, R. P., H. Servaes, and A. Tamayo (2014). "Have rating agencies become more conservative? Implications for capital structure and debt pricing". *The Journal of Finance* 69.5, pp. 1961–2005.

Batta, G. and V. Muslu (2017). "Credit rating agency and equity analysts adjustments to GAAP earnings". *Contemporary Accounting Research* 34.2, pp. 783–817.

Beaver, W., C. Shakespeare, and M. Soliman (2006). "Differential properties in the ratings of certified versus non-certified bond-rating agencies". *Journal of Accounting and Economics* 42.3, pp. 303–334.

Becker, B. and T. Milbourn (2011). "How did increased competition affect credit ratings?" *Journal of Financial Economics* 101.3, pp. 493–514.

Bharath, S. T. and T. Shumway (2008). "Forecasting default with the Merton distance to default model". *The Review of Financial Studies* 21.3, pp. 1339–1369.

Bolton, P., X. Freixas, and J. Shapiro (2012). "The credit ratings game". *The Journal of Finance* 67.1, pp. 85–111.

Bonsall, S., K. Koharki, and M. Neamtiu (2015). "The effectiveness of credit rating agency monitoring: Evidence from asset securitizations". *The Accounting Review* 90.5, pp. 1779–1810.

— (2017). "When do differences in credit rating methodologies matter? Evidence from high information uncertainty borrowers". *The Accounting Review* 92.4, pp. 53–79.

Bonsall, S. (2014). "The impact of issuer-pay on corporate bond rating properties: Evidence from Moody's and S&P's initial adoptions". *Journal of Accounting and Economics* 57.2, pp. 89–109.

Bonsall, S. B., J. Green, and K. A. Muller (2018). "Are credit ratings more rigorous for widely covered firms?" *The Accounting Review* 93.6, pp. 61–94.

Bozanic, Z., P. Kraft, and A. Tillet (forthcoming). "Qualitative corporate disclosure and credit analysts' soft rating adjustments". *European Accounting Review*.

Bruno, V., J. Cornaggia, and K. R. Cornaggia (2016). "Does regulatory certification affect the information content of credit ratings?" *Management Science* 62.6, pp. 1578–1597.

Cantor, R. and C. Mann (2003). "Measuring the Performance of Corporate Bond Ratings". *Moody's Special Comment*.

Cheng, M. and M. Neamtiu (2009). "An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility". *Journal of Accounting and Economics* 47.1, pp. 108–130.

Cornaggia, J. and K. Cornaggia (2013). "Estimating the costs of issuer-paid credit ratings". *Review of Financial Studies* 26.9, pp. 2229–2259.

deHaan, E. (2017). "The financial crisis and corporate credit ratings". *The Accounting Review* 92.4, pp. 161–189.

Dichev, I. and J. Piotroski (2001). "The long-run stock returns following bond ratings changes". *The Journal of Finance* 56.1, pp. 173–203.

Efing, M. and H. Hau (2015). "Structured debt ratings: Evidence on conflicts of interest". *Journal of Financial Economics* 116.1, pp. 46–60.

Fracassi, C., S. Petry, and G. Tate (2016). "Does rating analyst subjectivity affect corporate debt pricing?" *Journal of Financial Economics* 120.3, pp. 514–538.

Greene, W. (2010). “Testing hypotheses about interaction terms in nonlinear models”. *Economics Letters* 107.2, pp. 291–296.

Griffin, J. M. and D. Y. Tang (2012). “Did subjectivity play a role in CDO credit ratings?” *The Journal of Finance* 67.4, pp. 1293–1328.

He, J., J. Qian, and P. Strahan (2012). “Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities”. *The Journal of Finance* 67.6, pp. 2097–2137.

Hillegeist, S. A., E. K. Keating, D. P. Cram, and K. G. Lundstedt (2004). “Assessing the probability of bankruptcy”. *Review of Accounting Studies* 9.1, pp. 5–34.

Holthausen, R. and R. Leftwich (1986). “The effect of bond rating changes on common stock prices”. *Journal of Financial Economics* 17.1, pp. 57–89.

Hung, M., P. Kraft, S. Wang, and G. Yu (forthcoming). “Market Power and Credit Rating Standards: Global Evidence”. *Journal of Accounting and Economics*.

Jankowitsch, R., F. Nagler, and M. Subrahmanyam (2014). “The determinants of recovery rates in the US corporate bond market”. *Journal of Financial Economics* 114.1, pp. 155–177.

Jiang, J. X., M. H. Stanford, and Y. Xie (2012). “Does it matter who pays for bond ratings? Historical evidence”. *Journal of Financial Economics* 105.3, pp. 607–621.

Jorion, P., Z. Liu, and C. Shi (2005). “Informational effects of Regulation FD: Evidence from rating agencies”. *Journal of Financial Economics* 76.2, pp. 309–330.

Kedia, S., S. Rajgopal, and X. A. Zhou (2014). “Did going public impair Moody’s credit ratings”. *Journal of Financial Economics* 114.2, pp. 293–325.

— (2017). “Large shareholders and credit ratings”. *Journal of Financial Economics* 124.3, pp. 632–653.

Kraft, P. (2015a). “Do rating agencies cater? Evidence from rating-based contracts”. *Journal of Accounting and Economics* 59.2–3, pp. 264–283.

— (2015b). “Rating agency adjustments to GAAP financial statements and their effect on ratings and credit spreads”. *The Accounting Review* 90.2, pp. 641–674.

Kumar, A. (2010). “Self-selection and the forecasting abilities of female equity analysts”. *Journal of Accounting Research* 48.2, pp. 393–435.

Merton, R. C. (1974). “On the pricing of corporate debt: The risk structure of interest rates”. *The Journal of Finance* 29.2, pp. 449–470.

Moody’s Investors Service (2009). “Moody’s rating system in brief”.

Moody’s Investors Services (2006). “Moody’s approach to global standard adjustments in the analysis of the financial statements for non-financial corporations–Part 1”.

Partnoy, F. (1999). “The Siskel and Ebert of financial markets: Two thumbs down for the credit rating agencies”. *Washington University Law Quarterly* 77.3, pp. 619–712.

— (2010). “Overdependence on credit ratings was a primary cause of the crisis”. *Working paper, San Diego University School of Law*.

Securities and Exchange Commission (2012). “Report to Congress: Credit rating standardization study, As required by Section 939(h) of the Dodd-Frank Wall Street Reform and Consumer Protection Act”. *Securities and Exchange Commission, Washington, DC*.

Sethuraman, M. (2019). “The effect of reputation shocks to rating agencies on corporate disclosures”. *The Accounting Review* 94.1, pp. 299–326.

Vazza, D. and N. Kraemer (2016). “2015 annual global corporate default study and rating transitions”. *Standard & Poor’s*.

Xia, H. (2014). “Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?” *Journal of Financial Economics* 111.2, pp. 450–468.

Xia, H. and G. Strobl (2012). “The issuer-pays rating model and ratings inflation: Evidence from corporate credit ratings”. *Working paper, University of Texas at Dallas and University of Vienna.*

Appendix A Variable definitions and sources

This table presents the definitions of the variables used in our analyses. The variables are ordered alphabetically.

Variable	Definition
$Analyst\ Age$	Minimum of the first year of employment minus 22 years and the first year of college minus 18 years.
$Analyst\ Tenure:\ Firm$	The number of years between the date an analyst covers a firm for the first time and the date on which the quarter ends.
$Analyst\ Tenure:\ Industry$	The number of years between the date an analyst covers a company in the industry in which the rated firm operates for the first time (Fama French 49 classification) and the date on which the quarter ends.
$Analyst\ Tenure:\ Agency$	The number of years between the date an analyst starts working for the rating agency and the date on which the quarter ends.
$AssetBacked$	An indicator equal to one if a bond is an asset-backed issue and zero otherwise.
CAR	The cumulative abnormal return defined as the stock return minus the contemporaneous return on the value-weighted market portfolio, calculated over the three-day event window (-1, +1), where day 0 is the effective date of a rating change (CRSP).
$Cash/Assets$	Cash and short-term investments divided by total assets (CHE / AT, Compustat).
$Chapter11$	An indicator variable equal to one if the default type is Chapter 11 bankruptcy, and zero otherwise (*DEF_TYP_CD*, Moody's Default and Recovery Database [DRD]).
$Convertible$	An indicator variable equal to one if the issue can be converted to the common stock (or other security) of the issuer, and zero otherwise (Mergent FISD).
$Coupon$	The initial annual payment for a bond expressed as a percentage of the face amount (*COUP_RATE*, DRD).
$CRSPBond$	CRSP 30-year bond annual return (CRSP).
$Days$	The natural log of the number of days since the previous rating change in the same direction (days is set equal to 1,200 if there are no bond revisions in the same direction in the sample period) (Mergent FISD).
$Debt/Assets$	The sum of long- and short-term debt divided by total assets ((DLTT + DLC) / AT, Compustat).
$DebtEquity$	The sum of long- and short-term debt divided by book value of equity; set equal to zero if negative ((DLTT + DLC) / CEQ, Compustat).
$Default_{t+k}$	An indicator variable equal to one if an issuer defaults over k-year period relative to period t, and zero otherwise (based on information from Moody's DRD).
$DefaultBarrier$	An assessment of distance to default, measured as short-term debt plus one half long-term debt, scaled by total assets (*[DLC + 0.5*DLTT] / AT*, Compustat).
$DefaultPrice$	Trading price of defaulted debt, expressed as a percentage of par, as of the default date for distressed exchanges, or 30 days after default for all other types of default (*DEF_PRICE*, Moody's DRD).

Variable definitions (*continued*)

Variable	Definition
$DistressedExchange$	An indicator variable equal to one if the default type is distressed exchange, and zero otherwise (*DEF_TYP_CD*, DRD, Moody's DRD).
$EBITDA/Sales$	Earnings before interest, taxes, depreciation, and amortization divided by total sales (EBITDA / SALE, Compustat).
EDF	Expected default frequency, the market-based credit measure from Hillegeist et al. (2004) (Compustat, CRSP).
$Enhance$	An indicator variable equal to one if the issue has the credit enhancement feature, and zero otherwise (Mergent FISD).
$Equity$	Market value of equity, measured as common shares outstanding times closing stock price, divided by total assets (*(CSHO * PRCC_F)* / AT, Compustat).
$E_{TypeI,AdjustedGrid}$	An indicator variable equal to one if the grid-based quantitative rating fails to predict an actual event of default for a bond issue based on a cutoff rating of Baa3, and zero otherwise. (Mergent FISD).
$E_{TypeII,AdjustedGrid}$	An indicator variable equal to one if the grid-based quantitative ratings falsely predicted default based on a cutoff rating of Baa3 for a bond issue, and zero otherwise. (Mergent FISD).
$Female$	An indicator variable set equal to one if the credit rating analyst's gender is female and zero otherwise.
GDP	The annual gross domestic product (Federal Reserve Bank of St. Louis).
$IGrade$	An indicator variable equal to one if a bond is revised from investment grade to speculative grade or vice versa, and zero otherwise (Mergent FISD).
$Intangibility$	Intangible assets divided by total assets ($INTAN$ / AT, Compustat).
$IntCov$	Earnings before interest, taxes, depreciation, and amortization divided by interest expense (EBITDA / XINT, Compustat).
$IntExp/EBITDA$	Total interest expense divided by earnings before interest, taxes, depreciation, and amortization; set equal to zero if negative (XINT / EBITDA, Compustat).
$LargeLoss$	An indicator variable equal to one if a firm experiences an annual loss equal or greater than 25% of total assets, and zero otherwise (Compustat).
Leverage	The sum of debt in current liabilities and long-term debt divided by total assets ((DLC + DLTT) / AT, Compustat)
$LAsset$	The natural logarithm of total assets (AT, Compustat).
$LDefaults$	The number of defaults in the year before a rating change (Mergent FISD).
$LEmployees$	The natural logarithm of the number of employees (*EMP*, Compustat).
$LIssueAmt$	Natural logarithm of issue amount in $ millions (IssueAmt, Mergent FISD).
$LMediaCov$	Natural logarithm of the number of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date.
$LSales$	The natural logarithm of sales (SALE, Compustat).

Variable definitions (*continued*)

Variable	Definition
$LTDIssuance$	The ratio of long-term debt to total debt (*DLTT / [DLC + DLTT]*, Compustat).
$Maturity$	The time until the maturity of the bond in years (Mergent FISD).
MBA	An indicator variable set equal to one if the credit rating analyst has a master of business administration (MBA) degree and zero otherwise.
$NegRetain$	An indicator variable equal to one if a firm reports negative retained earnings, and 0 otherwise (Compustat).
$Non\,Top\,5\,MBA$	An indicator variable set equal to one if the credit rating analyst has a master of business administration (MBA) degree from a non-top five program and zero otherwise.
$\#\ Firms\ Covered$	The number of firms covered by the credit rating analyst at the end of the quarter.
$OperCF/Sales$	Operating activities net cash flow divided by total sales (OANCF / SALE, Compustat).
PostCrisis	An indicator variable equal to one for the post-July 2009 period, and zero otherwise.
$Profitability$	The profitability of the firm measured as earnings before interest, taxes, depreciation, and amortization (EBITDA), scaled by lagged total assets (*OIBDP / AT*, Compustat).
$ProfitMargin$	Operating income after depreciation and amortization divided by revenue (OIADP / REVT, Compustat)
Put	An indicator variable equal to one if the bondholder has the option, but not the obligation, to sell the security back to the issuer under certain circumstances, and zero otherwise (Mergent FISD).
$QuantRating_{Adj}$	Moody's grid-based rating (Moody's Financial Metrics).
Rating	Moody's issuer rating mapped to natural numbers such that higher numbers indicate higher rating quality, i.e., C = 1, ..., Aaa = 21 (www.moodys.com).
RChange	The absolute magnitude of the rating change (Mergent FISD).
Receivables	Total receivables divided by total assets (*RECT / AT*, Compustat).
Redeem	An indicator variable equal to one if the issue is redeemable under certain circumstances, zero otherwise (Mergent FISD).
$S\&P500$	The level of the Standard & Poor's 500 Index.
Senior	An indicator variable equal to one if the debt instrument is a senior security, and zero otherwise (*DEBT_SENR_CD*, DRD, Moody's DRD).
Secured	An indicator variable equal to one if the debt instrument is secured, and zero otherwise (*DEBT_SENR_CD*, DRD, Moody's DRD).
SeniorSecured	An indicator variable equal to one if the debt instrument is senior and secured, and zero otherwise (*DEBT_SENR_CD*, DRD, Moody's DRD).
Size	Natural logarithm of bond issue amount (in millions of dollars)
$SoftAdj$	Moody's soft rating adjustment (Moody's Financial Metrics).
$SoftAdjustAvoidE_{TypeI}$	An indicator variable equal to one if the Moody's soft rating adjustments ($SoftAdj$) avoids an otherwise missed default indicated by the grid-based rating, and zero otherwise.

Variable definitions (*continued*)

Variable	Definition
$SoftAdjustAvoidE_{TypeII}$	An indicator variable equal to one if the Moody's soft rating adjustments ($SoftAdj$) avoids an otherwise falsely identified default indicated by the grid-based rating, and zero otherwise.
$SoftAdjIndicator$	An indicator variable equal to one if an issuer's rating change is driven solely by a change in an issuer's soft rating adjustment, and zero otherwise.
$Subordinated$	An indicator variable equal to one if the debt instrument is subordinated, and zero otherwise (*DEBT_SENR_CD*, DRD, Moody's DRD).
$Top\ 5\ MBA$	An indicator variable set equal to one if the credit rating analyst has a master of business administration (MBA) degree from a top five program and zero otherwise (Top five MBA programs are from the 2011 *Economist* ranking and include University of Chicago, Tuck School of Business, Haas School of Business, University of Virginia, and IESE Business School).
$YSpread$	The initial offering yield spread on a corporate bond (Mergent FISD).

Figure 1
The components of credit ratings

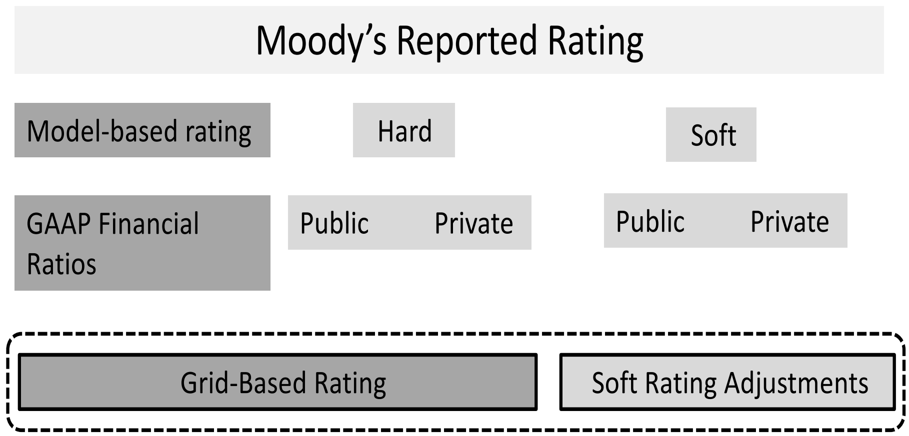

Figure 1 shows the composition of assigned credit ratings. As indicated, ratings include model-based ratings, hard adjustments, and soft adjustments. Model-based ratings are determined by GAAP financial ratios. Hard (e.g., non-GAAP adjustments to financial ratios) and soft adjustments (e.g., quality of managers or corporate governance) include information that is public and private. Grid-based ratings are the combination of model-based ratings and hard adjustments.

Table 1
Descriptive statistics

Panel A: Sample construction

Default sample (Type I error)		
Description	Bonds dropped	Remaining bonds
Defaulting bonds covered by Mergent FISD during 2003–2015		2,584
Less:		
Missing Compustat GVKEY	-44	2,540
Missing Compustat coverage for fiscal period prior to default	-362	2,178
Not rated by Moody's Investors Service	-502	1,676
Not covered by Moody's Financial Metrics	-471	1,205
Insufficient data to compute EDF	-413	792

Non-default sample (Type II error)		
Description	Bond-years dropped	Remaining bond-years
Non-defaulting bond-years covered by Mergent FISD during 2003–2015		391,165
Less:		
Missing Compustat GVKEY	-1,927	389,238
Missing Compustat coverage for fiscal period	-155,578	233,660
Not rated by Moody's Investors Service	-49,413	184,247
Not covered by Moody's Financial Metrics	-55,637	128,610
Insufficient data to compute EDF	-38,424	90,186

Panel B: Sample statistics

	Type I error sample							
			Full sample			Mean within EDF partition		
	Mean	Std. Dev.	Q1	Median	Q3	>Median	<Median	Diff.
$SoftAdjAvoidE_{TypeI}$	0.323	0.468	0.000	0.000	1.000	0.401	0.246	0.155*
$E_{TypeI,AdjustedGrid}$	0.442	0.497	0.000	0.000	1.000	0.462	0.422	0.040
EDF	0.052	0.101	0.000	0.002	0.077	0.103	0.000	0.103***
$PostCrisis$	0.468	0.223	0.000	0.000	1.000	0.416	0.519	-0.103
$MediaCov$	401.937	669.244	0.000	89.000	504.000	146.381	654.925	-508.544
$Asset$ ($ millions)	13,360.694	14,471.974	1,887.485	5,590.858	24,422.010	3,209.190	23,410.173	-20200.984***
$IntCov$	1.776	5.811	-1.657	1.358	3.640	-1.927	5.442	-7.369***
$DebtEquity$	3.338	17.397	0.370	0.945	2.172	5.646	1.053	4.592
$LargeLoss$	0.071	0.257	0.000	0.000	0.000	0.142	0.000	0.142*
$NegRetain$	0.434	0.496	0.000	0.000	1.000	0.533	0.337	0.196
$Size$ ($ millions)	390.193	311.515	175.000	300.000	500.000	297.138	482.312	-185.174***
$AssetBacked$	0.025	0.157	0.000	0.000	0.000	0.020	0.030	-0.010
$Convertible$	0.018	0.132	0.000	0.000	0.000	0.025	0.010	0.015
$SeniorSecured$	0.061	0.239	0.000	0.000	0.000	0.086	0.035	0.051
$Enhance$	0.295	0.457	0.000	0.000	1.000	0.315	0.276	0.038
Put	0.003	0.050	0.000	0.000	0.000	0.005	0.000	0.005
$Redeem$	0.848	0.359	1.000	1.000	1.000	0.807	0.889	-0.082
$Maturity$	6.923	4.602	4.065	6.461	8.467	6.370	7.470	-1.100*
GDP	16,457.431	786.365	15,731.689	16,129.418	17,305.752	16,424.433	16,490.097	-65.664
$CRSPBond$	0.072	0.042	0.048	0.061	0.100	0.075	0.069	0.005
$S\&P500$	1,623.477	358.838	1,240.183	1,476.010	2,030.797	1,600.714	1,646.011	-45.297
$LDefaults$	95.389	127.681	64.000	74.000	93.000	119.305	71.714	47.591*

	Type II error sample							
			Full sample			Mean within EDF partition		
	Mean	Std. Dev.	Q1	Median	Q3	>Median	<Median	Diff.
$SoftAdjAvoidE_{TypeII}$	0.078	0.268	0.000	0.000	0.000	0.121	0.035	0.086***
$E_{TypeII,AdjustedGrid}$	0.260	0.439	0.000	0.000	1.000	0.409	0.112	0.298***
EDF	0.004	0.018	0.000	0.000	0.000	0.007	0.000	0.007***
$PostCrisis$	0.527	0.279	0.000	1.000	1.000	0.515	0.538	-0.022
$MediaCov$	2,505.292	5,051.287	96.000	526.000	1,581.000	2,865.057	2,146.642	718.415
$Asset$ ($ millions)	89,948.262	154211.218	8,061.900	23,682.002	84,895.992	83,336.304	96,539.729	-13203.425
$IntCov$	8.243	15.326	1.986	3.418	7.337	5.679	10.799	-5.120
$DebtEquity$	1.694	2.432	0.638	1.163	2.346	1.901	1.489	0.412*
$LargeLoss$	0.006	0.079	0.000	0.000	0.000	0.013	0.000	0.013***
$NegRetain$	0.191	0.393	0.000	0.000	0.000	0.236	0.146	0.090
$Size$ ($ millions)	277.725	348.518	30.000	175.000	350.000	268.117	287.303	-19.185
$AssetBacked$	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000
$Convertible$	0.000	0.015	0.000	0.000	0.000	0.000	0.000	0.000
$SeniorSecured$	0.047	0.212	0.000	0.000	0.000	0.044	0.051	-0.007
$Enhance$	0.122	0.327	0.000	0.000	0.000	0.150	0.094	0.056***
Put	0.023	0.148	0.000	0.000	0.000	0.018	0.028	-0.010**
$Redeem$	0.561	0.496	0.000	1.000	1.000	0.549	0.572	-0.022
$Maturity$	6.430	7.308	1.078	4.153	9.128	5.929	6.929	-1.000*
GDP	16,281.853	773.835	15,671.967	16,220.667	17,047.098	16,161.307	16,402.024	-240.717**
$CRSPBond$	0.064	0.094	0.002	0.067	0.149	0.068	0.059	0.009
$S\&P500$	1,524.004	354.093	1,280.759	1,414.397	1,926.869	1,450.949	1,596.833	-145.883***
$LDefaults$	184.621	259.405	64.000	74.000	139.000	228.385	140.992	87.392***

Table 1 reports descriptive information for the Type I and Type II errors samples. Panel A reports the sample construction process. Panel B reports sample distributional statistics. All variables are defined in the Appendix.

Table 2
Univariate descriptives for Moody's credit rating and soft adjustments

Panel A: Average soft adjustments by default risk level

Default issuers

	$\overline{SoftAdj}$
Month relative to default:	
-24	-0.1838
-21	-0.4876
-18	-0.4500
-15	-0.6938
-12	-0.8729
-9	-1.3167
-6	-2.4202
-3	-2.4528
F-test:	
$\overline{SoftAdj}_{t-3} = \overline{SoftAdj}_{t-24}$	239.14***

Non-default issuers

	$\overline{SoftAdj}$
EDF decile:	
1	-0.0621
2	0.0603
3	-0.3618
4	-0.3831
5	-0.4235
6	-0.6524
7	-1.0258
8	-0.8888
9	-1.0996
10	-1.3436
F-test:	
$\overline{SoftAdj}_{Decile1} = \overline{SoftAdj}_{Decile10}$	21.09***

Panel B: Average EDF and soft adjustments by actual credit rating

	$\overline{EDF}$	$\overline{SoftAdj}$
Moody's rating:		
C	0.7056	-4.7368
Ca	0.5047	-5.8327
Caa3	0.3084	-2.4615
Caa2	0.1920	-2.4667
Caa1	0.1637	-1.4574
B3	0.0572	-0.8489
B2	0.0434	-0.9444
B1	0.0240	-0.7665
Ba3	0.0108	-0.8610
Ba2	0.0050	-1.0412
Ba1	0.0056	-0.5033
Baa3	0.0017	-0.4599
Baa2	0.0013	-0.1414
Baa1	0.0004	0.0182
A3	0.0005	0.1818
A2	0.0002	0.2082
A1	0.0005	0.1987
Aa3	0.0000	0.5070
Aa2	0.0000	0.9667
Aa1	0.0000	1.1034
Aaa	0.0000	1.1818

Table 2 reports cross-tabulations of average Moody's soft adjustments ($SoftAdj$) and expected default frequencies (EDF) based on the market-based credit risk measure from Hillegeist et al. (2004). Panel A reports the average value of $SoftAdj$ each quarter for the eight quarters leading to a default for the Type I error (default) analysis sample and for each decile of EDF for the Type II error (non-default) analysis sample. Panel B reports the average value of EDF and $SoftAdj$ for each Moody's credit rating category for the Type II error analysis sample. All variables are defined in Appendix A.

Table 3
Greater rating accuracy for higher default risk (e.g., higher EDF) issuers – Type I errors

	(1) $SoftAdjAvoidE_{TypeI}$		(2) $E_{TypeI,AdjustedGrid}$	
EDF	9.8409***	(2.92)	-1.8488	(-0.62)
$PostCrisis$	1.7815*	(1.68)	-0.8163	(-0.90)
$LMediaCov$	0.1347***	(2.68)	0.0642	(1.57)
$EDF \times PostCrisis$	8.4720***	(3.77)	-1.1319	(-0.67)
$EDF \times LMediaCov$	2.1862***	(4.05)	-0.2128	(-0.40)
$LAsset$	-0.1352	(-0.91)	-0.1122	(-0.74)
$IntCov$	-0.1253***	(-3.04)	-0.0073	(-0.25)
$DebtEquity$	-0.0234*	(-1.74)	-0.0199**	(-2.21)
$LargeLoss$	-1.5028***	(-2.58)	-0.6703	(-1.41)
$NegRetain$	0.1357	(0.47)	-0.0151	(-0.05)
$Size$	-0.0068	(-0.04)	0.1794	(0.96)
$AssetBacked$	-0.0351	(-0.87)	-0.0299	(-1.10)
$Convertible$	-0.1169	(-1.45)	-0.0997*	(-1.84)
$SeniorSecured$	-0.0164	(-0.41)	-0.9035*	(-1.73)
$Enhance$	0.1454	(0.63)	-0.1401	(-0.68)
Put	-0.2337**	(-2.18)	-0.1994***	(-2.76)
$Redeem$	0.5080	(1.08)	-0.0361	(-0.10)
$Maturity$	-0.0119	(-0.41)	-0.0073	(-0.43)
GDP	-0.0029*	(-1.78)	-0.0011	(-0.81)
$CRSPBond$	4.5459	(1.16)	-0.8309	(-0.26)
$S\&P500$	0.0062*	(1.90)	0.0019	(0.70)
$LDefaults$	0.0028**	(2.37)	0.0013	(1.34)
Constant	36.0767*	(1.70)	14.9125	(0.81)
Observations	792		792	
Pseudo R^2	0.453		0.040	
Area under ROC	0.758		0.572	

Table 3 provides the results from a logit regression examining the relationship between issuers' missed default events and estimated default frequencies. In column (1), the dependent variable is an indicator equal to one if the Moody's soft rating adjustments ($SoftAdj$) avoid an otherwise missed default indicated by the grid-based rating, and zero otherwise ($SoftAdjAvoidE_{TypeI}$). In column (2), the dependent variable is an indicator equal to one if the grid-based quantitative rating fails to predict an actual event of default for a bond issue based on a cutoff rating of Baa3, and zero otherwise ($E_{TypeI,AdjustedGrid}$). The primary variable of interest, EDF, is the expected default frequency computed as in Hillegeist et al. (2004). $PostCrisis$ is an indicator variable that is equal to one for ratings measured on or after July 1, 2009 and zero otherwise. $LMediaCov$ is the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All firm specific variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4
Greater rating accuracy for higher default risk (e.g., higher EDF) issuers – Type II errors

	(1) $SoftAdjAvoidE_{TypeII}$		(2) $E_{TypeII,AdjustedGrid}$	
EDF	5.5779***	(5.64)	12.5446**	(2.50)
$PostCrisis$	1.2288**	(2.12)	0.8955	(1.54)
$LMediaCov$	0.1920***	(3.09)	0.0572	(1.01)
$EDF \times PostCrisis$	3.1677***	(3.16)	3.5207	(1.34)
$EDF \times LMediaCov$	0.8445**	(2.29)	1.6782	(0.75)
$LAsset$	-0.2031*	(-1.69)	-0.7950***	(-5.34)
$IntCov$	-0.1837***	(-5.50)	-0.2773***	(-7.49)
$DebtEquity$	-0.0398	(-0.78)	0.0569	(1.43)
$LargeLoss$	-0.9093	(-1.58)	-2.6269***	(-3.33)
$NegRetain$	-0.2435	(-0.55)	0.9236**	(2.07)
$Size$	0.0108	(0.14)	0.2616*	(1.78)
$SeniorSecured$	-0.8559*	(-1.66)	-0.3011	(-0.85)
$Enhance$	-0.7865**	(-2.33)	0.6697***	(3.97)
Put	-0.1703	(-0.73)	-0.3028	(-1.53)
$Redeem$	-0.7834***	(-5.33)	-0.0578	(-0.27)
$Maturity$	0.0134	(1.48)	-0.0231***	(-3.27)
GDP	-0.0016	(-1.48)	-0.0021**	(-2.20)
$CRSPBond$	4.0909**	(2.01)	3.0767*	(1.90)
$S\&P500$	0.0042*	(1.66)	0.0053**	(2.34)
$LDefaults$	0.0012**	(2.11)	0.0006	(0.88)
Constant	18.9555	(1.49)	31.0786***	(2.82)
Observations	90,186		90,186	
Pseudo R^2	0.389		0.415	
Area under ROC	0.778		0.895	

Table 4 provides the results from logit regressions examining the relationship between issuers' false default predictions and default risk. In column (1), the dependent variable is an indicator equal to one if the Moody's soft rating adjustments ($SoftAdj$) avoid an otherwise falsely identified default indicated by the grid-based rating, and zero otherwise ($SoftAdjAvoidE_{TypeII}$). In column (2), the dependent variable is an indicator equal to one if the the grid-based quantitative ratings falsely predicted default based on a cutoff rating of Baa3 for a bond issue, and zero otherwise ($E_{TypeII,AdjustedGrid}$). The primary variable of interest, EDF, is the expected default frequency computed as in Hillegeist et al. (2004). $PostCrisis$ is an indicator variable that is equal to one for ratings existing on or after July 1, 2009. $LMediaCov$ is the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All firm specific variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5
Greater rating accuracy for higher default risk (e.g., higher EDF) issuers – Issuer default prediction

	(1)		(2)	
	$Default_{t+1}$		$Default_{t+3}$	
EDF	13.1025**	(2.26)	12.0154*	(1.87)
$SoftAdjust$	-0.4440***	(-2.95)	-0.4596***	(-3.29)
$QuantRating_{Adj}$	-0.4158***	(-4.39)	-0.4889***	(-5.15)
$EDF \times SoftAdjust$	-4.2972**	(-2.55)	-4.9187***	(-3.45)
$EDF \times QuantRating_{Adj}$	1.1233	(0.79)	2.1574	(1.61)
$PostCrisis$	-0.3953**	(-2.11)	-0.2462	(-1.37)
$LMediaCov$	-0.0458	(-0.87)	-0.0582	(-1.10)
$EDF \times PostCrisis$	-0.1419	(-0.03)	1.7343	(0.31)
$EDF \times LMediaCov$	-1.1199	(-0.88)	-1.0104	(-0.82)
$SoftAdjust \times PostCrisis$	-0.4678***	(-4.23)	-0.3471***	(-3.35)
$SoftAdjust \times LMediaCov$	-0.0746***	(-3.42)	-0.0652***	(-3.16)
$QuantRating_{Adj} \times PostCrisis$	-0.0083	(-0.15)	0.0190	(0.34)
$QuantRating_{Adj} \times LMediaCov$	0.0155	(1.05)	0.0218	(1.50)
$EDF \times SoftAdjust \times PostCrisis$	-1.1490***	(-3.64)	-1.7393***	(-2.72)
$EDF \times SoftAdjust \times LMediaCov$	-0.4158***	(-2.77)	-0.6189**	(-2.56)
$EDF \times QuantRating_{Adj} \times PostCrisis$	0.3761	(0.33)	0.4394	(0.38)
$EDF \times QuantRating_{Adj} \times LMediaCov$	-0.3690	(-1.24)	-0.2769	(-1.11)
$LSales$	-0.0683	(-0.30)	-0.0978	(-0.48)
$LAsset$	0.5408**	(2.50)	0.5613***	(2.88)
$Cash/Assets$	3.6210	(1.00)	2.6906	(0.81)
$(Cash/Assets)^2$	-14.2742	(-1.40)	-13.2467	(-1.38)
$EBITDA/Sales$	0.2403	(0.27)	0.1444	(0.24)
$(EBITDA/Sales)^2$	-1.8704	(-0.87)	-0.9809	(-0.70)
$OperCF/Sales$	0.6844	(0.40)	0.0579	(0.04)
$(OperCF/Sales)^2$	-2.1656	(-0.68)	-1.4364	(-0.61)
$IntExp/EBITDA$	0.0001	(0.85)	0.0001	(1.03)
$(IntExp/EBITDA)^2$	-0.0000	(-0.54)	-0.0000	(-0.80)
$Leverage$	-1.7348	(-0.73)	-1.2669	(-0.56)
$(Debt/Assets)^2$	2.5869	(1.13)	1.9407	(0.88)
Constant	-7.3761***	(-5.46)	-7.2268***	(-5.73)
Observations	5,342		5,342	
Pseudo R^2	0.107		0.122	
Area under ROC	0.739		0.758	

Table 5 provides the results from logit regressions of future issuer defaults on ratings and the interaction of ratings with issuer risk of default. The dependent variable, $Default_{t+k}$, is an indicator variable equal to one if an issuer defaults over the k-year period relative to period t, and zero otherwise. The variables of interest include $SoftAdjust$, the Moody's soft rating adjustment, and EDF, the expected default frequency computed as in Hillegeist et al. (2004). $PostCrisis$ is an indicator variable that is equal to one for ratings existing on or after July 1, 2009. $LMediaCov$ is the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All firm specific variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6

Greater rating accuracy for higher default risk (e.g., higher EDF) issuers – Default recovery losses

	Rating $t-1$		Rating $t-2$	
	(1)		(2)	
	$DefaultPrice$		$DefaultPrice$	
EDF	34.8187	(0.75)	29.4914	(0.18)
$SoftAdj$	7.3365***	(2.96)	2.5717***	(2.99)
$QuantRating_{Adj}$	9.2282***	(6.59)	10.8502***	(3.05)
$EDF \times SoftAdj$	49.3445**	(2.47)	32.8577*	(1.97)
$EDF \times QuantRating_{Adj}$	2.9704	(0.06)	2.9224	(0.04)
$PostCrisis$	5.3252	(1.54)	1.2757	(0.14)
$LMediaCov$	-3.1999	(-1.23)	-5.9840	(-1.69)
$EDF \times PostCrisis$	176.3921	(1.60)	-114.9828	(-0.69)
$EDF \times LMediaCov$	-19.8496	(-1.17)	23.7341	(0.56)
$SoftAdj \times PostCrisis$	6.9774**	(2.59)	2.1228***	(2.76)
$SoftAdj \times LMediaCov$	14.9139***	(7.25)	7.5653***	(4.93)
$QuantRating_{Adj} \times PostCrisis$	13.4114	(1.08)	5.2792	(0.95)
$QuantRating_{Adj} \times LMediaCov$	-5.2113	(-1.16)	2.8978	(1.23)
$EDF \times SoftAdj \times PostCrisis$	56.6659**	(2.76)	43.4056**	(2.55)
$EDF \times SoftAdj \times LMediaCov$	98.2452***	(2.94)	76.1390*	(1.87)
$EDF \times QuantRating_{Adj} \times PostCrisis$	-24.1922	(-1.04)	25.6792	(0.34)
$EDF \times QuantRating_{Adj} \times LMediaCov$	-27.9242	(-0.51)	7.0920	(0.53)
$Coupon$	1.6187*	(1.87)	-0.3568	(-0.35)
$SeniorSecured$	46.1690***	(2.96)	53.0637***	(5.70)
$Subordinated$	25.6614**	(2.61)	-1.7378	(-0.19)
$DistressedExchange$	-28.2204**	(-2.09)	49.9732**	(2.58)
$Chapter11$	-38.1513*	(-1.98)	20.5650	(1.58)
$Equity$	-12.3033	(-0.36)	69.3512***	(2.74)
$DefaultBarrier$	-30.2516	(-1.46)	-46.6680	(-1.07)
$LTDIssuance$	-42.4270*	(-1.86)	-27.9770	(-1.26)
$Profitability$	-66.8241***	(-3.14)	-107.7249*	(-1.94)
$Intangibility$	63.9623***	(5.10)	48.6764	(1.46)
$Receivables$	23.9722	(0.48)	97.2014***	(3.28)
$LAsset$	0.9420	(0.39)	-6.2181	(-1.63)
$LEmployees$	-3.7263*	(-1.82)	-8.3703**	(-2.60)
Year Fixed Effects	Yes		Yes	
Industry Fixed Effects	Yes		Yes	
Observations	351		420	
Adjusted R^2	0.899		0.783	

Table 6 provides the results from OLS regressions of default recoveries on pre-default discretion in credit ratings and the interaction of rating discretion with issuer pre-default risk of default. The dependent variable, $DefaultPrice$, is the trading price of defaulted debt, expressed as a percentage of par, as of the default date for distressed exchanges, or 30 days after default for all other types of default. The variables of interest include $SoftAdj$, the Moody's soft rating adjustment, EDF, the expected default frequency from Hillegeist et al. (2004), $PostCrisis$, an indicator variable that is equal to one for ratings measured on or after July 1, 2009 and zero otherwise, and $LMediaCov$, the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All firm-specific variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 7
Greater rating relevance for higher default risk (e.g., higher EDF) issuers – Offering yield spreads

	(1)	
	$YSpread$	
EDF	237.3712***	(2.94)
$SoftAdjust$	-28.8030***	(-6.27)
$QuantRating_{Adj}$	-34.7263***	(-9.30)
$EDF \times SoftAdjust$	-477.5709***	(-3.81)
$EDF \times QuantRating_{Adj}$	122.5147	(0.96)
$PostCrisis$	-129.6258*	(-1.80)
$LMediaCov$	-4.0967***	(-2.80)
$EDF \times PostCrisis$	-627.3894	(-0.76)
$EDF \times LMediaCov$	6.2235	(0.04)
$SoftAdjust \times PostCrisis$	-5.3369	(-1.11)
$SoftAdjust \times LMediaCov$	-1.8364**	(-2.08)
$QuantRating_{Adj} \times PostCrisis$	-1.9840	(-0.66)
$QuantRating_{Adj} \times LMediaCov$	0.6096	(1.22)
$EDF \times SoftAdjust \times PostCrisis$	-174.3087**	(-2.22)
$EDF \times SoftAdjust \times LMediaCov$	-60.0774***	(-3.50)
$EDF \times QuantRating_{Adj} \times PostCrisis$	-12.3898	(-0.09)
$EDF \times QuantRating_{Adj} \times LMediaCov$	-2.1732	(-0.10)
$Leverage$	55.2976**	(2.35)
$IntCov$	0.7659***	(4.92)
$ProfitMargin$	-112.7626***	(-4.93)
$LAsset$	-15.3334***	(-3.59)
$LIssueAmt$	23.4418***	(3.47)
$Maturity$	0.2056	(0.84)
$Senior$	-39.8471*	(-1.77)
$Secured$	34.1978	(1.38)
Year Fixed Effects	Yes	
Observations	2,455	
Adjusted R^2	0.667	

Table 7 reports the results from an OLS regression of offering yield spreads on credit ratings and the interaction of rating adjustments with issuer risk of default. The dependent variable, $YSpread$, is the initial offering yield spread on a corporate bond. The variables of interest include $SoftAdjust$, the Moody's soft rating adjustment, and EDF, the expected default frequency computed as in Hillegeist et al. (2004). $PostCrisis$ is an indicator variable that is equal to one for ratings existing on or after July 1, 2009. $LMediaCov$ is the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All firm specific variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 8
Greater rating relevance for higher default risk (e.g., higher EDF) issuers – Equity market reaction to rating changes

Panel A: Longer window returns prior to rating changes

	(1) $CAR_{-11,-1}$	(2) $CAR_{-120,-1}$	(3) $CAR_{-240,-1}$
Downgrades:			
Soft Adjustments	-0.004	-0.060**	-0.097**
Quant Rating	-0.024***	-0.117***	-0.227***
Difference	0.020*	0.057	0.130***
Upgrades:			
Soft Adjustment	0.004	0.062***	0.162***
Quant Rating	0.001	0.075***	0.184***
Difference	0.003	-0.013	-0.022

Panel B: Short-window returns regressions

	Downgrades (1) $CAR_{-1,+1}$		Upgrades (2) $CAR_{-1,+1}$	
$SoftAdjIndicator$	-0.0394***	(-3.31)	0.0522*	(1.87)
EDF	-0.4243***	(-2.89)	-0.1005	(-0.12)
$SoftAdjIndicator \times EDF$	-0.2694**	(-2.20)	0.1281*	(1.95)
$PostCrisis$	-0.0110	(-1.58)	0.0048	(0.78)
$LMediaCov$	-0.0037***	(-2.70)	0.0006	(0.23)
$SoftAdjIndicator \times PostCrisis$	-0.0217***	(-2.74)	0.0212	(0.23)
$SoftAdjIndicator \times LMediaCov$	-0.0052***	(-2.71)	-0.0022	(-0.49)
$EDF \times PostCrisis$	-0.2115*	(-1.67)	0.0248	(0.12)
$EDF \times LMediaCov$	-0.0128***	(-3.56)	0.0786	(0.54)
$SoftAdjIndicator \times EDF \times PostCrisis$	-0.0912***	(-4.71)	0.1932	(0.24)
$SoftAdjIndicator \times EDF \times LMediaCov$	-0.0470***	(-2.98)	-0.1208	(-0.48)
$RChange$	-0.0135**	(-2.46)	0.0050	(1.45)
$IGrade$	0.0072	(0.88)	0.0023	(0.41)
$Days$	0.0039	(1.20)	0.0001	(0.08)
Constant	-0.0158	(-0.64)	0.0002	(0.01)
Observations	1,714		1,490	
Adjusted R^2	0.148		0.042	

Table 8 reports analysis of equity returns around credit rating downgrades and upgrades based on whether they result solely from soft adjustments by Moody's or a change in the implied quantitative-based grid rating. Panel A reports mean cumulative abnormal returns for longer-window periods in advance of the rating changes. Panel B reports the results from OLS regressions of rating change announcement-period cumulative abnormal returns on an indicator for a change in rating adjustments and the interaction of the indicator for a change in rating adjustments with issuer risk of default. The dependent variable, CAR, is the cumulative abnormal return defined as the stock return minus the contemporaneous return on the value-weighted market portfolio, calculated over the three-day event window (-1, +1), where day 0 is the effective date of a rating change. The variables of interest include $SoftAdjIndicator$, an indicator variable equal to one if an issuer's rating change consists of only a change in an issuer's soft adjustment (i.e., $QuantRating_{Adj}$ remains the same), and zero otherwise, EDF, the expected default frequency computed as in Hillegeist et al. (2004), $PostCrisis$, an indicator variable that is equal to one for rating changes occurring on or after July 1, 2009, and $LMediaCov$, the natural logarithm of one plus the number of articles written about the issuer from RavenPack during the six months prior to the rating measurement date. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All firm specific variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 9

Credit rating agency analyst structure and issuer default risk

	(1) *MBA*	(2) *Top 5 MBA*	(3) *Non Top 5 MBA*	(4) *Female*	(5) *Analyst Age*	(6) *Analyst Tenure : Firm*	(7) *Analyst Tenure : Industry*	(8) *Analyst Tenure : Agency*	(9) *# Firms Covered*
EDF	4.9399***	5.5735***	3.2378**	4.7610***	8.5784**	-2.1157*	3.5273***	4.1513**	25.9491***
	(3.42)	(4.15)	(2.39)	(3.69)	(2.31)	(-1.92)	(2.93)	(2.23)	(4.55)
LMediaCov	0.4157***	0.1623**	0.1163*	0.1674**	1.2554***	-0.0942*	0.3932***	0.4897***	0.6173**
	(5.76)	(2.09)	(1.72)	(2.51)	(6.47)	(-1.93)	(6.89)	(3.89)	(2.46)
LAsset	0.0609	0.2662	-0.0348	-0.1671	0.1293	0.3463***	0.2457**	0.5564***	-0.1145
	(0.41)	(1.09)	(-0.24)	(-0.99)	(0.33)	(4.31)	(2.15)	(2.63)	(-0.24)
IntCov	-0.0138	-0.0728	0.0001	0.0297**	0.1223**	0.0075	-0.0030	0.0812***	-0.1759***
	(-0.99)	(-1.52)	(0.00)	(1.98)	(2.12)	(0.60)	(-0.22)	(3.80)	(-3.15)
DebtEquity	-0.0007	0.0025	-0.0015	0.0068***	-0.0161***	-0.0065*	-0.0045*	-0.0041	-0.0176
	(-0.24)	(0.75)	(-0.42)	(2.75)	(-4.34)	(-1.82)	(-1.94)	(-0.68)	(-1.13)
LargeLoss	-0.3736	-1.0483	-0.3503	0.3430	-3.2145	0.3080	-0.2584	2.2122***	-1.1550
	(-0.50)	(-0.80)	(-0.50)	(0.50)	(-1.64)	(0.69)	(-0.47)	(2.82)	(-0.40)
NegRetain	0.5964	-0.8790**	0.8089**	0.1838	1.2996	-0.1364	-0.5478*	0.0999	-0.6960
	(1.49)	(-2.02)	(2.11)	(0.51)	(1.44)	(-0.57)	(-1.70)	(0.15)	(-0.41)
GDP	0.0001	0.0020*	-0.0003	0.0000	-0.0021	0.0004	0.0018***	0.0012	-0.0143***
	(0.11)	(1.89)	(-0.67)	(0.10)	(-1.53)	(1.18)	(4.49)	(1.53)	(-6.06)
CRSPBond	-1.6258	2.7858	-2.3432	-1.5322	4.7684	-3.2334**	-4.3275***	-7.1405*	-3.7485
	(-0.99)	(1.55)	(-1.55)	(-0.70)	(0.91)	(-2.37)	(-2.82)	(-1.94)	(-0.49)
S&P500	0.0020	-0.0070***	0.0036**	0.0025	0.0056	-0.0001	-0.0017	-0.0048*	0.0096
	(1.38)	(-2.78)	(2.35)	(1.53)	(1.04)	(-0.10)	(-1.13)	(-1.79)	(1.35)
LDefaults	0.0003	-0.0015	0.0008	0.0005	0.0027	-0.0003	-0.0008	-0.0024*	-0.0037
	(0.47)	(-1.64)	(1.09)	(0.53)	(1.15)	(-0.56)	(-1.05)	(-1.70)	(-1.09)
Constant	-3.0679	-27.2524*	1.1844	-4.1024	66.2494***	-6.0016	-22.7334***	-8.2400	231.5088***
	(-0.48)	(-1.93)	(0.19)	(-0.66)	(4.42)	(-1.35)	(-4.78)	(-0.84)	(7.82)
Observations	4,883	4,883	4,883	4,883	4,883	4,883	4,883	4,883	4,883
Pseudo/Adjusted R^2	0.022	0.116	0.036	0.027	0.039	0.064	0.080	0.047	0.174

Table 9 presents the results from a series of logit and OLS regression estimations that attempt to link firm default risk to rating analyst quality. The dependent variables include Moody's rating analyst characteristics from Fracassi et al. (2016). *EDF* is an issuer's expected default frequency from Hillegeist et al. (2004) measured in year t. See Appendix A for all other variable definitions. Standard errors are clustered by firm. All variables have been winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.