# Issuer Default Risk and Rating Agency Conflicts*

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**Abstract**

This study examines whether rating agencies assign more stringent and accurate rating adjustments for issuers with higher default risk and whether this leads to adjustments that are more relevant to financial markets. We expect that rating agencies will make more informative subjective adjustments to limit their reputational risk for issuers with a higher likelihood of default—an event that can reveal the quality of assigned ratings. For defaulting issuers, especially those with a higher pre-failure default risk, we find that adjustments grow more stringent and accurate in the months leading up to default and better predict lender default recovery rates. For all issuers, we find that adjustments are more stringent and accurate as issuers' default risk grows. We also find that the relevance of adjustments increases with issuers' default risk, as evidenced by adjustments being more predictive of issuer default and offering yields and an increased market reaction to adjustment changes.

**Keywords:** credit rating agencies; rating adjustments; rating stringency; default

**JEL Classifications:** K00, G24, M40

# 1. Introduction

The major credit rating agencies are commonly criticized for assigning credit ratings that are untimely or that fail to accurately highlight borrowers' credit risk (e.g., Senate, 2002; Securities and Exchange Commission, 2003; White, 2010). The concern is typically centered around the issuer-pay model employed by the "Big Three" credit rating agencies (Standard and Poor's (S&P), Moody's Investors Service (Moody's), and Fitch Ratings (Fitch)), which can lead the credit rating agencies to issue inflated ratings for borrowers and delay downgrading issuers with declining credit quality. The concern is further exacerbated by the potential that the rating agencies' reputational costs of poor rating performance are insignificant because of heavy regulatory reliance on published credit ratings and the oligopolistic structure of the credit rating agency industry (Partnoy, 1999, 2010), coupled with rating agencies' success in avoiding significant penalties for failing to provide accurate credit ratings. If reputational concerns fail to discipline the major credit rating agencies, then reliance on firms' assigned credit ratings can potentially harm market participants. Recent empirical evidence supports these concerns (e.g., Jiang et al., 2012; Cornaggia and Cornaggia, 2013; Efing and Hau, 2015; Baghai and Becker, 2017, 2018).

The rating agencies, in contrast, argue that potential reputational costs are sufficient to offset the incentives created by the issuer-pay model (Covitz and Harrison, 2003; Senate, 2002; Securities and Exchange Commission, 2003). Academic research provides some support for this claim. For instance, Bolton et al. (2012) demonstrates analytically that investor discovery of inflated ratings will lead investors to punish a rating agency through lower reliance on its ratings. This can reduce future demand for its services, and thus future economic rents. Recent empirical evidence furthers this notion as deHaan (2017) shows that market participants reduced their reliance on corporate credit ratings after the 2008 financial crisis.[1] Also, prior empirical evidence provides support for the effect of reputational costs on credit rating properties in the settings of ratings-based contracts (Kraft, 2015a), of bank securitization (Bonsall et al., 2015), and of widely-covered issuers (Bonsall et al., 2018).

In this study, we examine whether subjective rating adjustments are used to limit reputational

[1] The Big Three should also, in theory, be subject to more market discipline in the coming years as The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 requires a reduction in regulatory reliance on firms' assigned credit ratings.

harm for issuers with a higher risk of default, a development that can reveal the quality of agency ratings. As demonstrated by Bolton et al. (2012), rating agencies are expected to trade off the short-term benefits of favoring issuers' interests (e.g., by providing inflated ratings) against the long-term costs from damaging their reputations, which can come from rating an issuer too highly prior to default or not providing a timely warning of default. We focus on qualitative rating adjustments, rather than the quantitative model-based component of ratings, of the major rating agencies as these adjustments are where ratings committees have the most discretion over assigned ratings (see Kraft, 2015a,b).[2] As Moody's explains, "quantification is integral to Moody's rating analysis, partially since it provides an objective and factual starting point for each rating committee's analytical discussion [...] However, Moody's ratings are not based on a defined set of financial ratios or rigid computer models. Rather, they are a product of comprehensive analysis of each individual issue and issuer by experienced, well-informed, impartial credit analysts" (Moody's Investors Service, 2016). If rating agencies respond to possible increased reputational costs for higher expected default risk issuers, we expect that rating agencies will go beyond standard rating models and make rating adjustments that are more stringent and accurate for such issuers. We also expect that such actions, particularly improvements in accuracy, should lead to more relevant ratings, which may include providing new information to financial markets.

Whether rating agencies take steps to safeguard their reputations for higher default risk issuers is unclear. Issuers with greater credit risk, especially those nearing default, are expected to place the greatest pressure on the rating agencies to maintain favorable credit ratings. This expectation is based on the increasing likelihood that such firms will violate covenants in bond indentures, supplier agreements, and union contracts, among others, which could force firms into bankruptcy. Credit rating agencies may cater to issuers' demands for inflated or inaccurate ratings in such circumstances through the opportunistic use of rating adjustments. The high-profile failures of Enron, Worldcom, Lehman Brothers, and asset-backed securities are just a few examples that critics have used to accuse rating agencies of engaging in such behavior (Partnoy, 2010). These criticisms cast doubt upon prior claims that the reputational risk the agencies face for failing to provide accurate credit risk assessments are significant. Hence, various mandatory changes to the

[2] The properties of Moody's ratings are the focus of our study because its ratings incorporate loss given default and Moody's discloses its qualitative and quantitative adjustments. While S&P also relies on both quantitative and qualitative analysis, S&P's assigned ratings in contrast do not incorporate loss given default.

credit rating industry have been proposed or implemented by regulators in recent years.

We measure rating adjustments as the difference between the actual rating and the predicted, or expected, rating from a benchmark rating model adapted from Baghai et al. (2014).[3] Our use of estimated rating adjustments is similar to the approach used by Griffin and Tang (2012) to asses the subjectivity of rating adjustments for collateralized debt obligations. Adjustments are optimistic when the actual rating is more favorable than the predicted rating from the benchmark model estimated for that year. These rating adjustments are comprised of both hard and soft adjustments.[4] Hard adjustments are quantitative in nature and typically made to recast financial ratios based on reported GAAP numbers to amounts more appropriate for judging credit risk, such as the capitalization of operating leases to assess an issuer's leverage. Conversely, soft adjustments are qualitative in nature and typically include items that require greater judgment, such as managerial ability (Bonsall et al., 2017a), governance, and internal controls, among others. We use estimated rating adjustments because actual adjustments are unavailable during most of our sample period of 1990–2015.[5]

Our first set of empirical tests focuses on a particularly interesting set of issuers: those that default. This group allows us to provide evidence regarding what actions the credit rating agencies take in the months leading up to default and whether rating adjustments aid in the prediction of actual losses following default. Using Moody's Default and Recovery Database for default dates and losses and Moody's ratings, we find that qualitative rating adjustments become increasingly more stringent (i.e., more pessimistic) leading up to events of default. The greater stringency is economically meaningful—in the two years preceding default the average rating adjustment results in approximately a one notch reduction in the actual rating (e.g., one rating notch equates to the numerical difference between A2 and A3 on the Moody's rating scale). We also examine a matched sample of issuers from the same year with the closest expected default frequency (EDF) that do not default within the next five years, which controls for potential default risk and year effects

[3]Prior research suggests that rating agencies have increased the stringency of their rating parameters over time, which has affected market-wide recovery rates (Alp, 2013). We control for the influence that increased stringency can have on our findings by estimating year-specific credit rating models throughout our analyses.

[4]See Kraft (2015b) for an extensive discussion regarding Moody's rating adjustments and how they relate to credit spreads and Kraft (2015a) for evidence of how rating adjustments are used opportunistically to cater to issuers with performance-priced loan contracts.

[5]We find, however, that our estimated adjustments share a 74 percent correlation with actual rating adjustments during the years that we have access to the actual adjustments, 2012–2015.

that could influence our findings. While we find evidence of rating pessimism with the matched non-defaulting firms over the same two-year period of time, we fail to find evidence of a trend in the rating adjustments for these matched non-defaulting firms. The difference in rating adjustments for default and non-default firms continues to provide evidence of greater stringency for default firms of similar magnitude. In addition, we find that the rate of Type I errors (i.e., missed defaults) is lower for issuers with greater default risk, measured using EDF. The improvement in actual ratings comes from rating adjustments rather than through model-based predicted ratings. Further, we find that rating adjustments are predictive of default losses, especially for issuers with greater pre-default credit risk. This evidence is important, as recovery rate estimation requires extensive judgement about the interplay among capital structure, creditor rights, jurisdiction, state law, and other forces in determining liquidation payouts.

Our second set of empirical tests focuses on all issuers. This group allows us to broaden our understanding of how default risk influences the bias, accuracy, and relevance of credit ratings without sampling only on issuers that are ex post known to default. Using Moody's ratings, we find that rating adjustments are more stringent for issuers with higher market-based expected default risk. For lower risk issuers, we find optimistic rating adjustments. In contrast, for higher risk issuers, we find pessimistic rating adjustments. This is consistent with the rating agencies acting defensively for issuers with a higher likelihood of default. In addition, we find that the rate of Type II errors (i.e., false default predictions) is lower for issuers with greater default risk. In this case, the improvement in actual ratings comes through rating adjustments offsetting the worsening ability of model-based predicted ratings to accurately capture non-default when default risk grows. These improvements contribute to rating adjustments being more relevant as default risk increases. Specifically, we find that ability of rating adjustments to predict default one and three years ahead increases for issuers with higher default risk. We find similar evidence when we alternatively examine how rating adjustments explain initial offering yields when default risk is higher. We also find that the stock market reaction to rating downgrades is incrementally stronger for downgrades that result solely from changes in rating adjustments when default risk increases. This suggests that the rating changes reveal private information and do not simply reflect public information already known to financial markets. We fail to find similar evidence for rating upgrades, which typically provide less information to financial markets (e.g., Holthausen and Leftwich, 1986).

Rather than our reputation-based explanation, an alternative possibility is that firms with greater default risk either voluntarily or at the rating agencies' request provide agencies with more information about their credit risk. Issuers may do so for several reasons: 1) restructuring and turnaround plans are typically put in place prior to the event of default; thus more information is typically available to be shared with credit rating agencies ex ante; 2) issuers may wish to reduce the likelihood of "surprise" default events because these can potentially cause panic among market participants and thus reduce recoveries in the liquidation process; and 3) greater information sharing pre-default can not only help determine the specific timing of default but also provide greater insight into the remaining entity's characteristics and competitiveness upon exiting the bankruptcy process.

To provide direct evidence that reputational concerns are important in our analyses, we examine whether rating improvements for higher default risk issuers are more pronounced in two settings where the credit rating agencies should be more concerned about their reputations. Relying on the findings of Becker and Milbourn (2011) that the dominant credit rating agencies (i.e., Moody's and S&P) provide lower quality ratings when industry competition from Fitch's coverage of new issuers is higher,[6] we examine if the improvement in ratings for higher default risk issuers is more pronounced when industry competition from Fitch is lower. In addition, relying on findings of deHaan (2017) of heightened reputational concerns by the ratings agencies following the financial crisis, we examine whether the improvement in the properties of the ratings for higher default risk issuers is more pronounced after the crisis. As predicted, we find evidence in most of our analyses that the improvement in ratings is larger when reputational concerns are relatively more pronounced. While not ruling out possible information sharing by issuers, this suggests that reputational concerns are responsible, at least in part, for our findings.

Our findings contribute to the growing literature on how reputational risk disciplines the credit rating agencies. We add to this literature by providing evidence that issuer default risk leads to subjective rating adjustments that are more stringent, accurate, and reveal more of rating agencies' private information. The improvement in rating quality observed before instances of issuer default suggests that these rare events provide strong incentives for the agencies to assign higher quality ratings (i.e., issuer defaults are closely scrutinized by various market participants such as investors,

[6]The evidence of Becker and Milbourn (2011) indicates that Moody's and S&P trade off their reputation for high quality ratings against lower future economic rents from lower coverage of new issuances.

competitors, regulators, and the media). The improvement in rating quality observed for public debt issuers in general suggests that the rating agencies take broad steps to avoid reputational harm from having optimistic or inaccurate ratings in place for issuers with a higher probability of default. Collectively, these findings support the general predictions of Bolton et al. (2012) that ratings quality should increase with the probability of the rating agencies "getting caught." These findings also are consistent with those of Xia (2014) that the ratings of issuer-paid agencies are slow to incorporate credit risk information unless, in their context, an investor-paid agency enters. While higher quality ratings arise because the more timely and informative investor-paid agency imposes reputational risk on the issuer-paid agency, our findings show that reputation risk can arise from the likelihood of issuer default rather than from the existence of conflicting ratings across agencies. We further add to this literature by showing that other issuer-pay model conflicts are exacerbated when detection risk is relatively low. In particular, Becker and Milbourn (2011) shows that industry competition from Fitch for new issues leads the rating agencies to risk their long-term reputations by issuing inflated ratings. In addition, deHaan (2017) finds that time periods with reduced scrutiny of the ratings agencies are associated with lower quality corporate ratings. Our results indicate that the rating agencies are more willing to cater to issuer interests in these instances when default is increasingly remote.

Our findings also have implications for recent research that explores on-going monitoring by the rating agencies. Bonsall et al. (2015) finds 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 (i.e., underwriters, regulators, legal representatives) subsides over time. Our findings suggest that the credit rating agencies make rating adjustments for higher default risk issuers that are more relevant and reveal more of rating agencies' private information, suggestive of continued borrower monitoring and enhanced information production by rating agencies. Collectively, our findings contribute to the ongoing debate concerning the structure of and incentives within the credit rating industry, particularly with regard to corporate debt securities.

In addition, we add to the emerging literature on the properties and importance of rating adjustments. Kraft (2015b) shows that the adjustments, despite their subjective nature, are associated with credit spreads and flatter credit spread term structures, consistent with lower issuer credit risk uncertainty. However, Kraft (2015a) finds that rating adjustments are used to cater to the incentives of issuers (e.g., rating adjustments are more favorable for issuers with loan contracts containing performance-pricing provisions) and that such catering is only partially muted when reputational costs are relatively higher. Our findings go further, providing evidence of strategic behavior that agency adjustments are used defensively for issuers with higher default risk.

## 2. Sample selection and primary variables

This section begins by describing the data sources used for our empirical tests. We then describe the construction of our rating adjustment variable. We next discuss the construction of our other primary variable, issuer expected default frequency.

### *2.1. Sample selection*

To calculate our measure of credit rating adjustments, we require firm-year data from Compustat to calculate the financial variables included in our rating model. We gather Compustat data from 1990–2015 and merge the data with credit rating data from Moody's Default and Recovery Database (DRD) available by subscription from Moody's Analytics. Across this time period, we obtain 26,758 observations representing 3,246 unique firms.

We obtain data on default events from the DRD, derived from Moody's own proprietary database of issuer, default, and recovery information. We use the default data, which provides the dates of default, the 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 firms in default, we start with the master default table (MAST_DFLT) consisting of 7,168 default events associated with 22,747 individual issues outstanding at the time of default (DFLT_ISSU) for global sovereign and corporate entities across all industries.[7] We limit our analyses to default events for U.S. publicly traded industrial firms and default types identified as distressed exchanges, Chapter 11 (re-organization) bankruptcy, and missed payments on interest or principal. Our baseline sample that examines rating adjustments in advance of default events includes 3,624 observations at the issue-default level. For our analysis of Type I errors related to default events, we merge our baseline sample of Moody's default

[7]The statistics are based on a data pull from DRD on August 8, 2015; The database is updated monthly.

ratings with data from the Mergent Fixed Income Securities Database (FISD) to provide control variables from Cheng and Neamtiu (2009) and other related studies. The resulting sample for the Type I error analysis is comprised of 3,336 observations at the issue-default level, which relate to 353 unique firms. Finally, for our analysis of default recoveries, we require non-missing information about loss given default from Moody's Analytics. There are 1,023 (1,022) observations with ratings one year (two years) in advance of default with recovery information.

Our second primary sample is based on all companies with Moody's credit ratings—both defaulting and non-defaulting firms. The second baseline sample includes all firm-years between 1990 and 2015 with a non-missing Moody's credit rating and expected default frequency information based on the approach in Hillegeist et al. (2004). There are a total of 19,546 firm-year observations for the baseline bias sample of both default and non-default firms. We next examine the frequency of Moody's Type II errors (overly pessimistic ratings) for non-defaulting firms. The sample for this analysis consists of all issue-year observations for which there is no default in the following one-year period. After requiring information for control variables from Cheng and Neamtiu (2009), the Type II error sample is comprised of 300,947 observations at the issue-year level. For our analysis of default prediction, we require firm-year observations for both defaulting and non-defaulting firms. After requiring information for control variables from Becker and Milbourn (2011), the default prediction sample is comprised of 18,689 observations at the firm-year level. For our analysis of bond offering yields, we require issue-level observations for newly issued non-convertible, fixed rate bonds from the Mergent FISD. After requiring information for all issuer and issue related control variables, the offering yield sample is comprised of 7,199 observations at the issue-level.

In addition to our primary analyses, we also examine the response of equity investors to rating changes as a function of credit risk. For this analysis, we require information about Moody's credit rating upgrades and downgrades. We obtain upgrade and downgrade information from the Mergent FISD. In cases of multiple rating changes per firm on a given day, we retain the largest magnitude rating change, consistent with the procedure used in Jorion et al. (2005). Following Jorion et al. (2005), our rating change sample is comprised of 7,778 downgrades and 4,798 upgrades at the issue-rating change level.

## *2.2. Rating adjustments*

Consistent with the reputation risk arguments of Bolton et al. (2012), as both the risk of default grows and the risk of investors learning of inflated ratings looms larger over time, credit rating agencies face an incentive to improve on their ratings to safeguard their reputations and avoid reduced future demand for their ratings. If credit rating agencies respond to this incentive, they may increasingly rely on their knowledge of issuers' creditworthiness by going beyond information conveyed by standard financial ratios. Figure 1 depicts the different components of credit ratings to illustrate how this can be accomplished. Rating agencies typically start with a hypothetical model-based rating using financial ratios based on reported GAAP amounts. Rating agencies then typically make hard and soft adjustments to arrive at their actual ratings (see Kraft, 2015b, for greater discussion).[8] Hard adjustments are typically quantitative-based adjustments to reported GAAP numbers (e.g., for off-balance-sheet debt) used to calculate standard financial ratios. Conversely, soft adjustments account for certain qualitative aspects of firms such as the strength of issuer management, governance, internal controls, and other internal and external factors that could affect the creditworthiness of the issuer. As Bozanic and Kraft (2017) demonstrates, some soft adjustments reflect managers' discussions in public financial disclosures. Other hard and soft adjustments can reflect private information provided by managers to the rating agencies.

To conduct our empirical tests, we require an estimate of rating adjustments because actual adjustments are available to us for only a limited portion of our sample period (discussed below). Similar in nature to the approach used in Griffin and Tang (2012) to estimate subjective rating adjustments for collateralized debt obligations, our measure of rating adjustments in Moody's issuer ratings is $RatingAdjust = Rating - \widehat{Rating}$, where $\widehat{Rating}$ is the predicted quantitative rating (denoted throughout as $QuantRating$). $RatingAdjust$ takes on positive (negative) values when actual ratings are more (less) favorable than predicted ratings. We estimate predicted credit ratings using the non-market-based variables from Baghai et al. (2014), which leads to the following ordered probit model:[9]

[8] 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.

[9] Our model does not include market-based determinants of credit ratings for two reasons. First, Moody's does not use such factors in their quantitative model-based assessment (Moody's Investors Service (2016)). Second, such factors could reflect the information in rating adjustments, which, if included, could lead us to inadvertently attribute such factors to $QuantRating$.

$$\begin{aligned}
Rating_{it} = {} & \alpha_0 + \alpha_1 IntCov_{it} + \alpha_2 Profit_{it} + \alpha_3 Book_Lev_{it} + \alpha_4 Log(Assets_{it}) + \alpha_5 Debt/EBITDA_{it} \\
& + \alpha_6 Neg.Debt/EBITDA_{it} + \alpha_7 Vol_{it} + \alpha_8 Cash/Assets_{it} + \alpha_9 ConvDe/Assets_{it} \\
& + \alpha_{10} Rent/Assets_{it} + \alpha_{11} PPE/Assets_{it} + \alpha_{12} CAPEX/Assets_{it} \\
& + \sum_j \delta_j Industry_j + u_{it} \qquad (1)
\end{aligned}$$

where *Rating* is coded from 1 to 21 (C to Aaa); *Rating* is the senior unsecured credit rating issued by Moody's.[10] We define all determinants of ratings in the Appendix, which are measured using annual amounts reported prior to the actual rating. For purposes of our rating stringency analysis, we estimate equation (1) cross-sectionally by year to allow rating standards to vary through time. Throughout our analyses, we use robust standard errors clustered by firm and include industry fixed effects, unless otherwise specified.

Panel A of Table 1 presents descriptive statistics for the 26,758 firm-year observations used to estimate our rating model. The average credit rating in this sample is 11.5, placing the average firm at the top end of the speculative range (Ba1). Firms in this sample can, on average, cover their interest expense over ten times with earnings before interest, taxes, depreciation, and amortization (EBITDA). EBITDA averages over 18 percent of revenues for sample firms. Debt represents, on average, roughly 40 percent of total assets. The average firm has total assets of $3.9 billion. Total debt is, on average, 3.7 times firms' EBITDA with more than three percent of firms having negative EBITDA. The standard deviation of operating income over the most recent five years averages over twelve percent of revenues. Cash and short-term marketable securities average seven percent of total assets. Convertible debt represents over one percent of total assets. Rent expense averages 1.6 percent of total assets. Firms' net property, plant, and equipment is, on average, 38 percent of total assets. Firms' capital expenditures average nearly six percent of total assets.

In Panel B we present the pooled regression estimates for equation (1). Firms that have higher interest coverage, lower book leverage, are larger, have lower debt relative to profitability, are profitable, have less cash, less convertible debt, lower rent payments, more tangible assets, and engage in more capital spending receive more favorable credit ratings, on average. This is as

[10] In tests in which we use an issue-based rather than issuer-based sample, we control for issue-specific characteristics, such as face value or seniority of the issue. Our issuer-level approach to measuring *RatingAdjust* should not be problematic for our tests because "notching" related to issuer-specific characteristics does not vary with the fundamentals of an issuer.

expected as firms that are larger, more profitable, have more tangible assets, and less debt are typically considered more creditworthy.

We assess the reasonableness of our estimation approach in two ways. First, we examine the validity of the estimated rating adjustments by looking at the correlation between *RatingAdjust* and Moodys' actual rating adjustments for the years 2012–2015, the only years for which we are able to collect the actual Moody's rating adjustments as introduced by Kraft (2015a,b). In untabulated analysis, we find that the correlation between the two measures is reasonably high at 74 percent. Second, we more closely examine the predictive ability of our model. In untabulated analysis, we find that if we alternatively use ordinary least squares the adjusted $R^2$ is 55.7 percent. We conduct this alternative estimation because the tabulated pseudo $R^2$ of 15.3 percent does not reflect the proportion of the variance explained by the model and, accordingly, should be interpreted with caution. Both of these descriptive statistics indicate that our rating modeling approach is fairly accurate at separating Moody's actual ratings into the two components.

### *2.3. Expected default frequency*

The other primary variable in our tests is expected default frequency, $EDF$. The expected default frequency is estimated following the Merton (1974) model using the approach in Hillegeist et al. (2004). Similar to other related research (e.g., Kedia et al., 2014; Xia, 2014; Bonsall et al., 2015; Kedia et al., 2017), we use this market-based measure of default risk, which should be less likely to reflect the strategic behavior of the rating agencies than actual ratings. The $EDF$ measure has an important limitation, however. As Bharath and Shumway (2008) demonstrate, estimated Merton (1974) model default probabilities are not strongly related to bond yields in the presence of actual credit ratings. This is consistent with EDF measures being rather imprecise due to the strict assumptions of the Merton (1974) model not being met. Accordingly, the use of $EDF$ could lead to a reduced ability in our tests to detect differences in issuer default risk.

## 3. Rating adjustments for defaulting issuers

This section examines whether credit rating agencies take actions to improve their rating adjustments for issuers as they approach default. We provide evidence regarding the optimism in rating adjustments in the months prior to default. We also provide evidence of whether rating adjustments are more accurate and relevant for predicting default recovery losses for issuers with a higher expected default frequency.

### *3.1. Do rating adjustments become less optimistic prior to default?*

Credit rating agencies state that their reputations are their most valuable asset (Covitz and Harrison, 2003). While prior research suggests that incentives related to the issuer-pay model or regulatory reliance on ratings could reduce the strength of reputational concerns in regulating rating agencies' behavior, failing to detect default is likely to impose the most reputational harm on the rating agencies. In light of this, we examine whether rating stringency increases as default nears. We estimate the following OLS model:

$$\begin{aligned} RatingAdjust_{it} = & \phi_1 Default_{t-3mo} + \phi_2 Default_{t-6mo} + \phi_3 Default_{t-9mo} \\ & + \phi_4 Default_{t-12mo} + \phi_5 Default_{t-15mo} + \phi_6 Default_{t-18mo} \\ & + \phi_7 Default_{t-21mo} + \phi_8 Default_{t-24mo} + \varsigma_{it} \end{aligned} \quad (2)$$

The intercept is omitted in equation (2) to allow the inclusion of indicator variables, $Default$, for the eight three-month time periods prior to default. H1 predicts that rating stringency increases as default approaches. We test this over the one and two years prior to default—i.e., $\phi_1$—$\phi_4$<0 and $\phi_1$—$\phi_8$<0, respectively. The dependent variable $RatingAdjust_{it}$ is a quarterly measure of rating adjustments, which is calculated as the difference between the actual rating and the latest annual predicted quantitative rating. This approach is consistent with the major rating agencies use of at least annual (and often multi-year averages of) financial ratios for purposes of determining credit ratings .[11]

Possible credit risk differences or time trends could confound our inferences. To alleviate such concerns, we use a control group of comparison firms that have the closest expected default frequency, $EDF$, to the defaulting firms and that have outstanding debt two years prior to the sample

[11] As Moody's (Moody's Investors Service, 2018) indicates "As a rule of thumb, we are looking through the next economic cycle or longer. Because of this, our ratings are not intended to ratchet up and down with business or supply-demand cycles or to reflect last quarter's earnings report." As a practical matter, the use of more recent financial information to construct $RatingAdjust_{it}$ does not lead to fundamental differences in the measure. Specifically, when we estimate Eq. (1) using quarterly, rather than annual, data, the alternative $RatingAdjust$ measure has a 94 percent correlation with the $RatingAdjust$ measure used in our empirical tests.

firm's default event but do not default within the following five years after the sample firm's default event date and re-estimate equation (2). We then test whether $\phi_1$—$\phi_4$ and $\phi_1$—$\phi_8$ for the default firms systematically differ relative to the non-default firms. Because ratings adjustments are, by construction in equation (1), uncorrelated with standard model-based determinants of credit risk, we do not include control variables in equation (2).

Column (1) of Table 2 presents the results from the estimation of equation (2). We find that the average value for *RatingAdjust* 24 months prior to default is -1.23 notches, providing evidence that Moody's rating adjustments are pessimistic. In addition, while rating stringency increases as the default date approaches as predicted by H1, we note that the largest magnitude changes in rating adjustments occur in the one-year period prior to default. For instance, roughly 79 percent of the 0.90 notch increase in rating stringency from month $t-24$ through $t-3$ occurs in the one-year period prior to default. As shown in Table 2, these differences are statistically significant.

Moving to the matched non-default firms presented in column (2), we find that their rating adjustments are negative and statistically significant in each period. We also find that the rating adjustments are relatively unchanged over time. In contrast, the changes in the differenced rating adjustments in column (3) grow increasingly pessimistic in the months leading up to default. Tests of the differences, shown at the bottom of column (3) are statistically significant. Collectively, the evidence in Table 2 suggests that in the two years prior to default, reputational concerns lead Moody's to increase rating stringency using rating adjustments and that it does so early enough to warn rating users that these firms are approaching default.

### *3.2. Are rating adjustments more accurate for higher EDF issuers?*

We next examine whether rating adjustments result in lower missed default predictions (i.e., Type I errors) for issuers with higher default risk using following logit regression:

$$E_{TypeI} = \vartheta_0 + \vartheta_1 EDF_{it} + \vartheta_2 X_{it} + u_{it} \tag{3}$$

where $E_{TypeI}$ is an indicator variable equal to one if agency ratings failed to predict an actual event of default for a bond issue, and zero otherwise. Our primary variable of interest is the expected default frequency, $EDF$, measured one year prior to an event of default. If issuers with higher expected default frequencies are of greater concern to rating agencies, then we expect a negative coefficient on $EDF$. Importantly, as our focus is on the effect of subjective rating adjustments, we need to remove from actual ratings the changing properties of ratings arising improvements or declines in model-based ratings. To accomplish this, we separately examine the frequency of errors using actual ratings, $E_{TypeI,Actual}$, and model-based ratings, $E_{TypeI,QuantRating}$. The difference in error rates across the two dependent variables captures the extent to which rating adjustments improve rating accuracy. Accordingly, the difference in coefficients for $EDF$ across the $E_{TypeI,Actual}$ and $E_{TypeI,QuantRating}$ estimations is our test of whether rating adjustments lead to more accurate default predictions for higher default risk issuers. $X$ is 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.[12] We define these variables in the Appendix.

Table 3 presents the results from estimating equation (3). Column (1) presents results for our Type I error analysis using actual ratings, $E_{TypeI,Actual}$, while column (2) presents results for our Type I error analysis using model-based ratings, $E_{TypeI,QuantRating}$. The coefficient estimate for $EDF$ in column (1) is statistically negative, suggesting that credit rating agencies more accurately assess firms' likelihood of default as the risk of default increases. In contrast, the coefficient estimate for $EDF$ in column (2) is negative but insignificant. We formally test whether the difference in the two $EDF$ coefficient estimates is significant using a $\chi^2$ test. As indicated in the last row of the table, the $EDF$ coefficient estimate is larger in absolute value for actual ratings. This evidence suggests that rating agencies use subjective rating adjustments to increase the accuracy of default prediction for higher risk issuers. In terms of magnitude, the Type I error rate for actual ratings is 8.3 percentage points lower for firms at the third quartile value of $EDF$ compared to that for firms at the first quartile value of $EDF$. This difference in error rate is approximately 11.6 percent of the overall Type I error rate of 71.4 percent for firms at the median value of $EDF$. Regarding our controls, we find that $Log(Assets)$, $IntCov$, $NegRetain$, $SeniorSecured$, $Enhance$, $Redeem$, $GDP$, and $S\&P500$ are also important determinants of Type I errors.

[12] We do not control for whether the issue can be converted to the common stock (or other security) of the issuer, as none of the default issues have a conversion option.

### *3.3. Do rating adjustments better predict default recovery losses for higher EDF issuers?*

Given the observed differences in the bias and accuracy of rating adjustments for issuers prior to default, we next provide evidence regarding whether these properties lead to ratings that are more relevant to 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 default recovery rates for specific types of default as identified by the Moody's DRD: Chapter 11 liquidation and restructuring, distressed exchanges, and payment defaults.[13] For each event, we examine whether rating adjustments predict creditor recovery rates. Similar to Jankowitsch et al. (2014), we examine recovery rates for default events using the following OLS regression model:

$$\begin{aligned} DefaultPrice_{it} = {} & \delta_0 + \delta_1 RatingAdjust_{it} + \delta_2 QuantRating_{it} + \delta_3 EDF_{it} \\ & + \delta_4 RatingAdjust_{it} \times EDF_{it} + \delta_5 QuantRating_{it} \times EDF_{it} \\ & + \delta_6 X_{it} + \delta_4 X_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \end{aligned} \tag{4}$$

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 adjustments are informative about loss recovery prior to default, we expect the coefficient for *RatingAdjust* to be positive. We expect that model-based ratings estimated prior to default events are associated with lower recovery rates and, accordingly, the coefficient for *QuantRating* to be positive. Moreover, we expect that rating adjustments will be relatively more informative for issuers with greater default risk and, thus, we predict the coefficient for the interaction $RatingAdjust \times EDF$ to be positive. We allow for the interaction $QuantRating \times EDF$ in this test, and subsequent tests, but do not make a directional prediction. $X$ is set of control variables similar to those used in Jankowitsch et al. (2014) and include factors for bond, default-type, and issuer characteristics. We also include industry ($\alpha_i$) and year ($\alpha_t$) fixed effects.

Table 4 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 $t-2$.

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

In both columns, the coefficient estimates on $RatingAdjust$ are statistically positive, consistent with more favorable rating adjustments leading to higher lender recoveries in bankruptcy. We also find that the coefficients on $QuantRating$ are statistically positive, consistent with model-based credit ratings providing incremental information about future recoveries from defaulted issuers. In addition, we find that the coefficient for the interaction $RatingAdjust \times EDF$ is statistically positive. This indicates that rating adjustments have a greater correspondence with eventual default recovery rates for issuers with greater potential default risk. In terms of magnitude, the estimated coefficient on $RatingAdjust \times EDF$ is significant, with an interquartile increase in $EDF$ implying an increase in the association between $DefaultPrice$ and $RatingAdjust$ of 0.341, which represents an increase of approximately 20.1 percent over the association when $EDF$ is at its sample mean value.[14] Consistent with prior research (e.g., Jankowitsch et al., 2014), we find that default recovery amounts are also explained by $SeniorSecured$, $DistressedExchange$, $Chapter11$, $LTDIssuance$, and $Log(Assets)$.

## 4. Rating adjustments and default risk (All issuers)

In this section, we present our second set of empirical analyses focusing on all issuers (default and non-default). This group allows us to broaden our understanding of the effects of default risk on rating adjustments without sampling only on issuers that are ex post known to default. In our tests, we again focus on how the bias, accuracy, and relevance of rating adjustments varies with expected default risk.

### *4.1. Are rating adjustments less optimistic for higher EDF issuers?*

Similar to our analysis of how agency rating adjustments become increasingly more stringent prior to actual defaults, we examine whether rating adjustments become more stringent as default risk grows. For this analysis, we again use $EDF$ as our measure of default risk as it is expected to be less

[14] These findings allow for somewhat different inferences than 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 accuracy of rating adjustments better predict default events. In contrast, the default recovery loss analysis provides evidence of when rating adjustments better predict actual credit losses.

affected by the strategic actions of the rating agencies. Our empirical test of whether the stringency of rating adjustments grows with default risk is implemented by forming decile portfolios for $EDF$ and then testing whether average rating adjustments are more stringent for the bottom decile (highest expected default frequency) relative to the top decile (lowest expected default frequency). Our formal test is a univariate means tests of the difference.

Table 5 presents the results from our examination of whether default risk leads to more stringent ratings for a broad sample of firms. As shown in the table, we find that rating adjustments grow increasingly pessimistic as the expected default frequency grows. Specifically, the average $RatingAdjust$ for the top $EDF$ decile is 0.182 and is significantly greater than zero. This indicates that rating adjustments are optimistic, leading to higher actual ratings, for issuers with the lowest level of default risk. In contrast, the average $RatingAdjust$ for the bottom $EDF$ decile is -0.792 and is significantly less than zero. This indicates that rating adjustments are pessimistic for issuers with the highest level of default risk. The difference of almost a full rating notch across the two portfolio means is statistically significant, as indicated by the $F$-test statistic of 44.56 in the last row of the table. This evidence suggests that systematic bias in rating adjustments is pervasive and varies with the credit rating agencies' concern for having favorable adjustments in place for issuers with higher default risk.

### *4.2. Are ratings adjustments more accurate for higher EDF issuers?*

We next examine whether false default predictions (Type II errors) are lower for issuers with higher default risk. We expect that rating agencies will have more accurate rating adjustments due to the greater on-going monitoring of issuers with higher default risk in general. We investigate this using the following logit regression model:

$$E_{TypeII} = \chi_0 + \chi_1 EDF_{it} + \chi_2 X_{it} + \omega_{it} \tag{5}$$

where $E_{TypeII}$ is an indicator variable equal to one if a credit rating agency or the predicted credit rating model predicted a default event for a bond issue where one did not eventually occur, and zero otherwise. If the accuracy of ratings for issuers with higher $EDFs$ are of relatively greater concern to rating agencies, then Type II error rates should be lower; we measure $EDF$ one year prior to an event of non-default. We separately examine the frequency of Type II errors using actual ratings, $E_{TypeII,Actual}$, and model-based ratings, $E_{TypeII,QuantRating}$, with the difference in error rates capturing the effect of the rating adjustments on the improvement in ratings. If rating adjustments are used strategically to achieve more accurate non-default predictions, the $EDF$ coefficient for the $E_{TypeII,Actual}$ estimation is expected to be lower in absolute value than for the $E_{TypeII,QuantRating}$ estimation. Our control variables ($X$) 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).

Table 6 reports the results from our estimation of equation (5). Column (1) of Table 6 presents results for our Type II error analysis using actual ratings, while column (2) presents results for our Type II error analysis using quantitative model-based ratings. In column (1), the coefficient estimate for $EDF$ using actual ratings is insignificant. In contrast, the coefficient estimate for $EDF$ using model-based ratings is statistically positive, consistent with financial ratios falsely predicting default to a greater extant when issuer default risk grows. The estimated coefficient on $EDF$ in column (2) is consistent with a 62 basis point increase in the Type II error rate across third quartile and first quartile $EDF$ firms—an approximate 3.0 percent increase relative to the 20.4 percent Type II error rate at the median level of $EDF$. Combined, these findings indicate that the accuracy of model-based ratings declines with an issuer's expected default frequency, but that rating adjustments offset the reduction in accuracy. We formally test the difference in the estimated $EDF$ coefficients in the last row of Table 6 using a $\chi^2$; as the table shows, the lower Type II error rate for actual ratings when EDF grows is significant at conventional levels. Similar to our Type I analysis, we find that $Log(Assets)$, $IntCov$, $DebtEquity$, $LargeLoss$, $NegRetain$, $Size$, $SeniorSecured$, $Enhance$, $Redeem$, $Maturity$, $GDP$, $CRSPBond$, and $S\&P500$ are also significant determinants of Type II errors.

### *4.3. Are ratings adjustments more relevant for higher EDF issuers?*

In this sub-section, we investigate the relevance of rating adjustments in three important settings. We first provide evidence of whether rating adjustments better predict default for higher EDF issuers. Second, we provide evidence of whether rating adjustments better explain offering yields for higher EDF issuers. Third, we provide evidence of whether the market reaction to rating adjustment changes is larger for higher EDF issuers.

*4.3.1. Issuer default prediction*

The improvements in rating adjustments for issuers with greater default risk documented in subsection 5.2 could lead to ratings that are more predictive of actual defaults. We investigate the predictive ability of rating adjustments for future defaults with the following logit regression model:

$$\begin{aligned} Default_{it+k} = {} & \beta_0 + \alpha_1 RatingAdjust_{it} + \beta_2 QuantRating_{it} + \beta_3 EDF_{it} \\ & + \beta_4 RatingAdjust_{it} \times EDF_{it} + \beta_5 QuantRating_{it} \times EDF_{it} + \beta_6 X_{it} + u_{it} \end{aligned} \tag{6}$$

where $Default_{t+k}$ is a binary variable equal to one if a firm defaults alternatively over the one- or three-year period subsequent to period $t$, and zero otherwise. We expect that both rating adjustments and model-based ratings are predictive of future default events and, therefore, expect the coefficients on $RatingAdjust$ and $QuantRating$ to be positive. Further, our primary prediction is that 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 for the interaction $RatingAdjust \times EDF$ will be positive. Our test includes several control variables ($X$), as well as their squared terms, to control for the impact that various firm characteristics can have on firms' default probabilities. These variables follow those used in Becker and Milbourn (2011).

Table 7 presents the results of estimating equation (6). Column (1) presents results when defaults occur within the subsequent one-year period, while column (2) presents results when defaults occur in the subsequent three-year period. Across both columns, the coefficient estimates on both $RatingAdjust$ and $QuantRating$ are statistically negative. This suggests that less favorable rating adjustments and quantitative model-based rating components are associated with future issuer default. More importantly, the coefficient estimates on $RatingAdjust \times EDF$ in both columns are statistically negative. This indicates that analysts' rating adjustments are incrementally more informative as market-based default risk grows. In terms of magnitude, an interquartile range increase in $EDF$ implies an increase in the magnitude of the association between $RatingAdjust$ and $Default_{t+1}$ ($Default_{t+3}$) of 0.004 (0.005), which represents an increase of 29.6 (29.9) percent over the association at the mean level of $EDF$ implied by the estimated coefficient on $RatingAdjust$. We fail to find that the coefficient on $QuantRating \times EDF$ is statistically significant. Our controls are generally insignificant, with the exception of $(EBITDA/Sales)^2$. This is consistent with

*RatingAdjust* and *QuantRating* already capturing the information included in the control variables.

#### *4.3.2. Initial offering yields*

We also investigate whether rating adjustments for issuers have higher default risk better reflect the information in offering yields. We explore the relevance of rating adjustments for bond offering yields in the following OLS regression specification:

$$\begin{aligned} YSpread = {} & \varsigma_0 + \varsigma_1 RatingAdjust_{it} + \varsigma_2 QuantRating_{it} + \varsigma_3 EDF_{it} \\ & + \varsigma_4 RatingAdjust_{it} \times EDF_{it} + \varsigma_5 QuantAdjust_{it} \times EDF_{it} + \varsigma_6 X_{it} + \iota_{it} \end{aligned} \tag{7}$$

where $YSpread$ is the initial offering yield on a newly issued bond. Issuers with higher rating adjustments and model-based quantitative ratings should have lower yield spreads. This leads to the prediction of negative coefficients for *RatingAdjust* and *QuantRating*. Moreover, for issuers with higher expected default frequencies, we expect that rating adjustments should be even more informative and, thus, we predict a negative coefficient for the interaction $RatingAdjust \times EDF$. $X$ is a set of control variables following Beaver et al. (2006) and includes various issuer and issue characteristics.

We report the results in Table 8. The coefficient estimates for *RatingAdjust* and *QuantRating* are significantly negative, consistent with more favorable rating adjustments and model-based ratings being associated with lower initial offering yield spreads. In addition, we find that the coefficient estimate on the interaction term $RatingAdjust \times EDF$ is statistically negative. This suggests that rating adjustments have a greater correspondence to the information reflected in offering yield spreads for issuers with higher default risk. The magnitude of the coefficient estimate on $RatingAdjust \times EDF$ implies that an interquartile range increase in $EDF$ increases the offering yield spread per notch of *RatingAdjust* by 1.05 basis points, a 3.3 percent increase over the association at the mean level of $EDF$ implied by the estimated coefficient on *RatingAdjust*. Although not predicted, we also find that the coefficient estimate on the interaction term $QuantRating \times EDF$ is statistically negative; however, in untabulated tests the coefficient estimate is significantly lower in absolute value than for $RatingAdjust \times EDF$. With the exception of $ProfitMargin$,

$Log(IssueAmt)$, and $Senior$, the control variables incrementally determine offering yield spreads.

#### *4.3.3. Equity market reaction to rating adjustment changes*

Our last analysis examines whether changes in rating adjustments reveal relatively more private information to equity market participants when they are made for issuers with higher default risk. We examine rating adjustments separately for those that lead to rating downgrades and upgrades using the following OLS regression model:

$$\begin{aligned} CAR_{it} = {} & \varphi_0 + \varphi_1 RatingAdjustIndicator_{it} + \varphi_2 EDF_{it} + \varphi_3 RatingAdjustIndicator_{it} \times EDF_{it} \\ & + \varphi_4 RChange_{it} + \varphi_5 IGrade_{it} + \varphi_6 Days_{it} + \tau_{it} \end{aligned} \tag{8}$$

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 $RatingAdjustIndicator$, an indicator variable equal to one if a firms' rating change is driven solely by a change in an issuer's rating adjustment, and zero otherwise. We expect that downgrades and upgrades driven only by changes in rating adjustments should lead to incrementally negative and positive market reactions, respectively. In addition, we expect that the market reaction will be more pronounced when issuer default risk is higher, as measured by EDF. Together, this leads to the prediction of negative (positive) coefficients for $RatingAdjustIndicator$ and the interaction $RatingAdjustIndicator \times EDF$ for rating downgrades (upgrades). Similar to Jorion et al. (2005), our controls take into account the magnitude of ratings changes (where the constant term reflects rating changes of one notch), revisions across the important investment-/speculative-grade threshold, and the length of time between rating revisions.

Table 9 presents our findings from estimating equation (8). Column (1) presents results for rating downgrades, while column (2) presents results for rating upgrades. In column (1), the coefficient estimate on $RatingAdjustIndicator$ is statistically negative, suggesting that downgrades driven solely by changes in rating adjustments lead to an incrementally negative equity market reaction. The coefficient estimate on $RatingAdjustIndicator \times EDF$ is also statistically negative, consistent with downgrades driven solely by changes in rating adjustments leading to even greater revisions by the market for issuers with higher default risk. The magnitude of the estimated coefficient on $RatingAdjustIndicator \times EDF$ implies that an interquartile range increase in $EDF$ is associated with an incrementally negative cumulative abnormal stock return of 3.2 percent over days $[-1, +1]$ relative to a credit rating downgrade compared to that for downgrades at the mean level of $EDF$. This represents a relative increase of over 185 percent. In column (2), we fail to find similar evidence for rating upgrades. The intercept is positive but insignificant, providing little evidence that the equity market reacts to rating upgrades. The lack of a significant equity market reaction to upgrades in general is similar to the findings of prior related research (Holthausen and Leftwich, 1986; Jorion et al., 2005). The size of the rating change and the number of days since the last rating change also explain the equity market reaction to rating downgrades.

Taken together, our findings indicate that rating adjustments are used defensively for issuers with higher default risk. The ratings of such issuers are more conservative, more accurate and better predict default recovery rates, actual default, and initial offering spreads. In addition, rating downgrades of such issuers reveal more private information to equity market participants.

## 5. Reputation or information sharing?

While our primary findings are consistent with a response to reputational concerns by the rating agencies, the possibility exists that defaulting issuers or higher default risk issuers provide rating agencies with greater information during the rating process. Specifically, firms that eventually default or face higher default risk could either voluntarily or at the request of credit rating agencies provide credit rating agencies with more information during the rating process. This could lead to more stringent, accurate, and informative credit risk assessments for these firms.

Higher default risk issuers may engage in greater information sharing with credit rating agencies for multiple reasons. First, if issuers believe that default is looming or imminent, they will likely hire legal advisors and investment bankers, among others, to help prepare the firm for the eventual default and restructuring actions. Given this, much information is available to be shared with credit rating agencies ex ante. Second, failing to provide more granular information to credit rating agencies may result in "surprise" default events, which could result in panic pricing and selling among market participants. Thus, providing rating agencies with greater information pre-default can result in more efficient and lucrative creditor recoveries. Third, providing rating agencies with greater information to more accurately assess default risk can not only help determine the specific timing of default but also allow market participants to more accurately assess the surviving entity's characteristics and competitiveness upon exiting the bankruptcy process. Greater transparency pre-default may also have reputational benefits for managers both during and after bankruptcy proceedings. Finally, while credit rating agencies meet routinely with issuers to assess firms' overall credit risk (Bonsall et al., 2017b), conversations with credit rating agency personnel at both Moody's and S&P suggest that credit rating agencies meet with certain issuers more frequently if default risk is believed to be increasing over time. More frequent interaction could lead to greater information sharing with credit rating agency analysts.

Industry competition for ratings by Fitch can help distinguish between reputational concerns by Moody's and greater information sharing by issuers prior to default. Reputational harm arising from the discovery of inaccurate ratings prior to default is expected to be higher when the duopoly profits enjoyed by Moody's and S&P are less threatened. Specifically, Becker and Milbourn (2011) provide empirical evidence that Moody's and S&P assign more favorable credit ratings when Fitch rates a higher proportion of new issuances in an industry and that their ratings exhibit a lower ability to accurately predict default.[15] Other studies (Kedia et al., 2014; Dimitrov et al., 2015; Baghai and Becker, 2017) document findings that further support a reputation-based explanation for how competition from Fitch can lead to lower quality credit ratings. Such behavior by incumbent rating agencies is consistent with trading off reputation against lower future economic rents. Given this, greater rating agency competition provides us with a potentially powerful setting to examine whether heightened credit rating agencies' reputational concerns explain our findings.

In addition, the recent financial crisis exposed various deficiencies with regard to leading credit rating agencies' policies and procedures (deHaan, 2017), consistent with the prediction of rating confidence cycles (Mathis et al. (2009)). Certain failures by leading rating agencies led to significant regulatory changes, culminating with the implementation of the Dodd-Frank Wall Street Reform and Consumer Protection Act. Therefore, the financial crisis provides us with another potentially powerful setting to investigate a reputation-based explanation for our findings.

To probe further whether our primary findings support a reputation-based explanation, we

[15] Bae et al. (2015) fails to find evidence that differences in Fitch's market share lead to higher rating levels once (unobservable) industry characteristics are considered, particularly differences across regulated and unregulated industries. Our tests control for this concern.

modify our primary tests by interacting our primary variables of interest with *Reputation*, which is either the negative of Fitch Ratings' three-digit SIC industry market share ($Reputation = -1 \times FitchMktSh$), or a binary variable equal to one if observations occur in the post-July 2009 period, and zero otherwise ($Reputation = PostCrisis$).[16] These codings allow consistent interpretation of *Reputation*, with higher values representing instances when the rating agencies should be more concerned with their reputations.

Table 10 presents our results for the default sample with the main variables interacted with *Reputation*. Panel A provides the results for the changing bias in *RatingAdjust* in the months prior to default. In column (1), where $Reputation = -1 \times FitchMktSh$, we find that the coefficients for the interactions $Default_{t-k} \times Reputation$ are significantly negative, suggesting that the pessimistic adjustments prior to default are more pronounced when reputational concerns are greater. In column (2), where $Reputation = PostCrisis$, with exception of $Default_{t-18} \times Reputation$, the coefficients for the interactions are again significantly negative, providing further evidence that reputation concerns by the rating agencies lead to further rating stringency before default. Our findings are consistent with the results reported earlier in Table 2.

The Type I error results are presented in Panel B. Columns (1) and (2) present results for our Fitch market share analyses, while columns (3) and (4) present results for our pre- and post-financial crisis analyses. For the $E_{TypeI,Actual}$ analyses, the coefficient estimates on the interaction term $EDF \times Reputation$ in columns (1) and (3) are statistically negative. For the $E_{TypeI,QuantRating}$ analyses, the coefficient estimates on the interaction term $EDF \times Reputation$ in columns (2) and (4) are insignificant. Together, these findings indicate that rating adjustments are even more helpful at reducing missed default predictions by the credit rating agencies when reputation concerns are more pronounced. Our formal tests of the difference in *EDF* coefficients across the two dependent variables are presented at the bottom of the panel and are similar to those presented earlier.

Panel C presents the results for default recovery rates. For both measures of *Reputation*, we find in years $t-1$ and $t-2$ that the coefficient estimates for the interactions $RatingAdjust \times Reputation$ are significantly positive. In addition, for both measures of *Reputation*, we find in year $t-1$ in columns (1) and (3) that the coefficient estimates for the interactions $RatingAdjust \times EDF \times Reputation$ are significantly positive. Combined, this indicates that rating adjustments are more

[16] We follow deHaan (2017) and use July 2009 as the pre- and post-financial crisis cutoff date.

predictive of default recovery rates when reputational concerns are greater, and that this effect is even more pronounced for issuers with greater default risk. We fail to find similar evidence in year $t-2$. Similar to our primary tests, the coefficient estimates for $RatingAdjust$ and $QuantRating$ are significantly positive.

Table 11 presents our results for the full sample with the main variables interacted with $Reputation$. We provide evidence in columns (1) and (2) of Panel A that rating adjustments are more stringent when reputational concerns should be greater—i.e., when Fitch's market share of new issuances in the industry is lower and in the years following the financial crisis. However, the greater stringency, as indicated by the coefficients for the interaction of $EDF$ decile groupings with reputation, is not observed in all decile groupings. Further, the coefficients on the $EDF$ decile groupings are statistically negative for the groupings below Decile=4. Together, these findings indicate that reputation concerns are at least partially responsible for our earlier results.

Panel B of Table 11 presents results for the Type II error analysis. In columns (1) and (2), $Reputation = -1 \times FitchMktSh$, and in columns (3) and (4), $Reputation = PostCrisis$. The coefficient estimates on $EDF \times Reputation$ in columns (1) and (3) are statistically negative, using $E_{TypeI,Actual}$ as the dependent variable. In contrast, the coefficient estimates on $EDF \times Reputation$ in columns (2) and (4) are insignificant, using $E_{TypeI,QuantRating}$ as the dependent variable. This evidence indicates that rating adjustments lead to even further reductions in false default predictions when the rating agencies face greater reputation concerns. We continue to find that the differences in $EDF$ coefficients across the two dependent variables are significantly different, as shown in the last row of the panel.

In Panel C, we present the results from re-estimating our default prediction analysis. Columns (1) and (2) present results for our Fitch market share analyses, while columns (3) and (4) present results for our pre- and post-financial crisis analyses. The coefficient estimates on $RatingAdjust$ and $RatingAdjust \times EDF$ are both statistically negative in columns (1) and (2), which rely on $-1 \times FitchMktSh$ for reputational concerns. More importantly, the coefficient estimates on $RatingAdjust \times EDF \times Reputation$ are also statistically negative. In columns (3) and (4) the coefficient estimates for the same coefficients are statistically negative, which rely on $PostCrisis$ for reputational concerns. Combined, this evidence suggests that reputational concerns by the rating agencies lead to more informative rating adjustments, particularly for higher default risk issuers.

Panel D provides our findings from re-estimating our offering yield spread analysis. Column (1) presents results when Fitch market share is our proxy for reputation, while column (2) presents results when our post-crisis indicator variable is our proxy for reputation. The coefficient estimates on $RatingAdjust$ and the interaction $RatingAdjust \times EDF$ are statistically negative in both columns. Further, the coefficient estimates on the triple interaction $RatingAdjust \times EDF \times Reputation$ are both statistically negative. These results indicate that reputational concerns lead to an incremental improvement in rating informativeness for initial offering yield spreads.

In our final analysis, we present the results from re-estimating our stock market reaction to rating changes test in Panel E. In columns (1) and (2), $Reputation = -1 \times FitchMktSh$, and in columns (3) and (4), $Reputation = PostCrisis$. For downgrades, in column (1), the coefficient estimates for $RatingAdjustIndicator$, $RatingAdjustIndicator \times EDF$, and $RatingAdjustIndicator \times EDF \times Reputation$ are all statistically negative. Similar results are found in column (3), with the exception of the coefficient on $RatingAdjustIndicator \times EDF \times Reputation$ which is insignificant. For upgrades, in column (2), the coefficient estimates for $RatingAdjustIndicator$, $RatingAdjustIndicator \times EDF$, and $RatingAdjustIndicator \times EDF \times Reputation$ are all statistically positive. However, in column (4) we fail to find similar evidence. While these results suggest that rating agencies' adjustments are incrementally more informative to equity market participants when Fitch market share declines, we fail to find similar evidence of improved rating informativeness during the post-crisis period.

In sum, we find evidence that reputational concerns are, in part, responsible for our findings. These concerns by the rating agencies lead to significant changes in the bias, accuracy, and informativeness of rating adjustments for issuers with higher default risk. While this evidence does not completely rule out the possibility that issuers voluntarily or at the request of the rating agencies provide more private information about their credit risk, our evidence suggests that reputation concerns are an important mechanism driving the choices of rating agencies.

## 6. Conclusion

Credit rating agencies have faced considerable criticism following perceived rating failures in the early 2000s (e.g., Enron and Worldcom) and more recently with regard to failures related to asset-backed securities during the 2008 financial crisis. Critics of the major rating agencies suggest that conflicts of interest inherent to the issuer-pay compensation model cause leading rating agencies to assign inflated and untimely credit risk assessments of both issuers and securities. Conversely, rating agencies assert that their reputations are their most important assets and that maintaining their reputations prevents them from catering to issuers' desires for more favorable credit ratings.

Our study examines whether reputational concerns discipline credit rating agencies into making more conservative and accurate credit rating adjustments for issuers with higher default risk, leading to more relevant ratings. We focus on rating adjustments, which unlike the quantitative model-based component of ratings, reflect the subjective assessments of rating committees. Credit rating adjustments include both hard and soft adjustments. While hard adjustments typically account for quantitative firm characteristics, soft adjustments encompass qualitative firm characteristics and are thus more subjective in nature. If rating agencies are concerned about the reputational risk from failing to provide adequate credit risk assessments of issuers, the subjectivity inherent in these adjustments can allow credit rating agencies to become more conservative and accurate in their credit rating assessments as default approaches.

Consistent with greater default risk disciplining rating agencies, we find for a sample of defaulting issuers that rating adjustments become more stringent as the default date approaches and that missed default predictions are less frequent for issuers with higher pre-default credit risk. We also find that ratings adjustments are predictive of default recovery rates, especially for issuers with greater pre-default credit risk. In addition, for a broad sample of public debt issuers, we find that rating adjustments are more stringent and that false default predictions are lower for issuers with higher default risk. These improvements also lead to more relevant rating adjustments (i.e., they better predict future defaults, initial offering yield spreads, and have greater equity market reactions to rating downgrades). In further tests, we find that these results are more pronounced when reputational concerns should be more important (i.e., when industry competition is lower and following the financial crisis). Combined, these findings indicate that the rating agencies use rating adjustments to avoid potential reputational harm in the case of issuer default.

Our study offers several contributions. First, our findings extend prior research related to issuer-pay model conflicts by showing that issuer default risk mitigates opportunistic behavior by the rating agencies. This evidence is of particular interest given that higher default risk issuers are expected to apply the greatest pressure on the rating agencies for less stringent and less accurate ratings. Second, we provide evidence that on-going monitoring varies systematically by the default risk of the issuer and that increased monitoring leads to rating adjustments that are more relevant and release more of the rating agencies' private information to financial markets. Finally, while recent findings suggest that rating adjustments are used opportunistically, our findings imply that when reputational concerns for the rating agencies are arguably the greatest (i.e., when issuers face default) the rating agencies use their adjustments defensively.

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# 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 |
|---|---|
| *Book_Lev* | The sum of long- and short-term debt divided by total assets ((DLTT + DLC) / AT, Compustat).CAPEX/Assets Capital expenditures divided by total assets (CAPX / AT, Compustat).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). |
| $CAPEX/Assets$ | Capital expenditures divided by total assets (CAPX / AT, Compustat). |
| $CAR$ | 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]). |
| $ConvDe/Assets$ | Convertible debt divided by total assets (DCVT / AT, Compustat). |
| $Convertible$ | 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). |
| $Debt/EBITDA$ | The sum of long- and short-term debt divided by earnings before interest, taxes, depreciation, and amortization; set equal to zero if negative ((DLTT + DLC) / EBITDA, Compustat). |
| $Debt/Equity$ | 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 a firm 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). |

**Appendix A** (*continued*)

| Variable | Definition |
|---|---|
| $DefaultPrice$ | 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). |
| $DistressedExchange$ | 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). |
| $E_{TypeI}$ | An indicator variable equal to one if the actual rating ($E_{TypeI,Actual}$) or the model-based quantitative ratings ($E_{TypeI,QuantRating}$) failed to predict an actual event of default for a bond issue, and zero otherwise (Mergent FISD). |
| $E_{TypeII}$ | An indicator variable equal to one if the actual rating ($E_{TypeII,Actual}$) or the model-based quantitative ratings ($E_{TypeII,QuantRating}$) falsely predicted default for a bond issue, and zero otherwise (Mergent FISD). |
| $FitchMktSh$ | The proportion of new bond ratings issued by Fitch in year $t$ for firm *i's* two-digit NAICS industry (Mergent FISD). |
| $GDP$ | 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). |
| $Log(Defaults)$ | The number of defaults in the year before a rating change (Mergent FISD). |
| $Log(Assets)$ | The natural logarithm of total assets (*AT*, Compustat). |
| $Log(Employees)$ | The natural logarithm of the number of employees (*EMP*, Compustat). |
| $Log(IssueAmt)$ | Natural logarithm of issue amount in $ millions (IssueAmt, Mergent FISD). |
| $Log(Sales)$ | The natural logarithm of sales (SALE, Compustat). |
| $LTDIssuance$ | The ratio of long-term debt to total debt (*DLTT / [DLC + DLTT]*, Compustat). |

**Appendix A** (*continued*)

| Variable | Definition |
|---|---|
| $Maturity$ | The time until the maturity of the bond in years (Mergent FISD). |
| $Neg.Debt/EBITDA$ | An indicator variable equal to one if $Debt/EBITDA < 0$, and zero otherwise (Compustat). |
| $NegRetain$ | An indicator variable equal to one if a firm reports negative retained earnings, and 0 otherwise (Compustat). |
| $OperCF/Sales$ | 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. |
| $PPE/Assets$ | Net property, plant, and equipment divided by total assets (PPENT / AT, Compustat). |
| $Profit$ | Earnings before interest, taxes, depreciation, and amortization divided by sales (EBITDA / REVT, Compustat). |
| $Profitability$ | The profitability of the firm measured as earnings before interest, taxes, depreciation, and amortization (EBITDA), scaled by lagged total assets ($OIBDP$ / $AT$, 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). |
| $QuantRating$ | Expected credit ratings ($\widehat{Rating_{it}}$) estimated using the non-market based variables from Baghai et al. (2014). The determinants of ratings include interest coverage, profitability, book leverage, firm size, debt-to-profitability, negative debt-to-profitability; volatility of profitability, liquidity, convertible debt, off-balance sheet borrowing through operating leases, tangibility of assets, and capital expenditure. |
| $Rating$ | 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). |
| $RatingAdjust$ | The estimated Moody's total rating adjustment (i.e., $Rating - QuantRating$). |
| $RatingAdjustIndicator$ | An indicator variable equal to one if a firms' rating change consists of only a change in an issuer's qualitative credit rating (i.e., $QuantRating$ remains unchanged), and zero otherwise. |
| $RChange$ | 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). |
| $Rent/Assets$ | Rent expense divided by total assets (XRENT / AT, Compustat). |
| $Reputation$ | Reputation is either the negative of Fitch Ratings' three-digit SIC industry market share ($FitchMktSh$), or a binary variable equal to one if observations occur in the post-July 2009 period, and zero otherwise ($PostCrisis$). |
| $S\&P500$ | 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). |

**Appendix A** (*continued*)

| Variable | Definition |
|---|---|
| *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). |
| *Subordinated* | An indicator variable equal to one if the debt instrument is subordinated, and zero otherwise (*DEBT_SENR_CD*, DRD, Moody's DRD). |
| $Vol$ | Standard deviation of $Profit$ over the prior five fiscal years; a minimum of two years required (Compustat). |
| $YSpread$ | The initial offering yield on a debt instrument (Mergent FISD). |

**Figure 1**
The Components of Credit Ratings

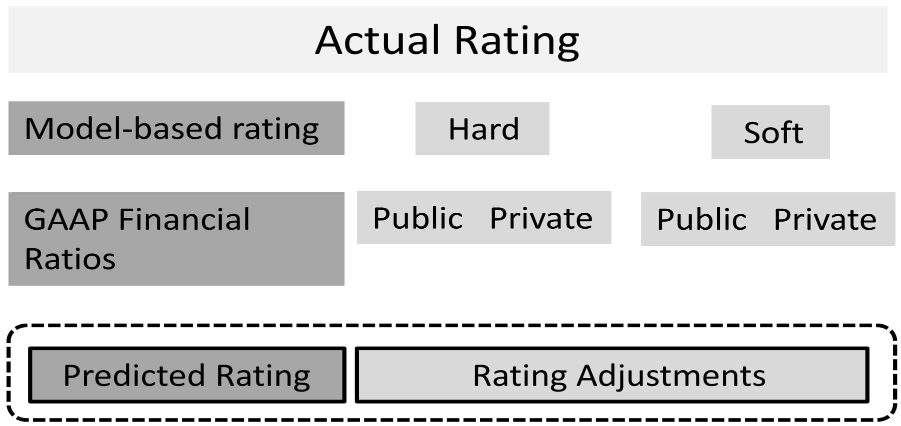


Figure 1 shows the composition of assigned credit ratings. As indicated, ratings include model-based ratings, hard adjustments, and soft adjustments. The model-based rating is determined by GAAP financial ratios. Hard (e..g., non-GAAP adjustments to financial ratios) and soft adjustments (e.g., quality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

## Table 1

Ratings model descriptives and estimation

Table 1 provides information related to estimates of our predicted credit rating model. Panel A presents descriptive statistics for the variables used in the model. Panel B presents the pooled estimation of the predicted rating ordered probit model over the 1990–2015 period. Our later analyses rely on annual estimations of the same model to construct total rating adjustments in Moody's issuer ratings ($RatingAdjust = Rating - \widehat{Rating}$), where $\widehat{Rating}$ is the predicted quantitative rating (denoted throughout as $QuantRating$). Industry fixed effects are included based on Fama and French (1997) industry definitions. See the Appendix for 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.

*Panel A: Descriptive statistics*

| | (1) Mean | (2) Std. Dev. | (3) Q1 | (4) Median | (5) Q3 |
|---|---|---|---|---|---|
| $Rating$ | 11.486 | 4.051 | 8.000 | 12.000 | 15.000 |
| $IntCov$ | 10.044 | 33.188 | 2.607 | 4.907 | 9.282 |
| $Profit$ | 0.186 | 0.645 | 0.101 | 0.172 | 0.286 |
| $Book\_Lev$ | 0.393 | 0.244 | 0.237 | 0.346 | 0.492 |
| $Log(Assets)$ | 8.287 | 1.556 | 7.172 | 8.216 | 9.368 |
| $Debt/EBITDA$ | 3.724 | 6.236 | 1.599 | 2.894 | 4.805 |
| $Neg.Debt/EBITDA$ | 0.034 | 0.182 | 0.000 | 0.000 | 0.000 |
| $Vol$ | 0.123 | 1.660 | 0.013 | 0.024 | 0.044 |
| $Cash/Assets$ | 0.074 | 0.094 | 0.012 | 0.039 | 0.099 |
| $ConvDe/Assets$ | 0.012 | 0.044 | 0.000 | 0.000 | 0.000 |
| $Rent/Assets$ | 0.016 | 0.028 | 0.002 | 0.008 | 0.016 |
| $PPE/Assets$ | 0.382 | 0.271 | 0.141 | 0.342 | 0.619 |
| $CAPEX/Assets$ | 0.059 | 0.060 | 0.022 | 0.044 | 0.076 |

*Panel B: Rating model estimation*

| | (1) $Rating$ |
|---|---|
| $IntCov$ | 0.0061*** |
| | (4.05) |
| $Profit$ | 0.0136 |
| | (0.51) |
| $Book\_Lev$ | -3.0014*** |
| | (-17.53) |
| $Log(Assets)$ | 0.7040*** |
| | (23.77) |
| $Debt/EBITDA$ | -0.0789*** |
| | (-13.66) |
| $Neg.Debt/EBITDA$ | -3.3831*** |
| | (-17.76) |
| $Vol$ | -0.0141 |
| | (-1.95) |
| $Cash/Assets$ | -1.3708*** |
| | (-4.46) |
| $ConvDe/Assets$ | -1.5357*** |
| | (-3.41) |
| $Rent/Assets$ | -5.9437*** |
| | (-5.17) |
| $PPE/Assets$ | 0.9197*** |
| | (4.20) |
| $CAPEX/Assets$ | 1.7491** |
| | (2.88) |
| Industry Fixed Effects | Yes |
| Observations | 26,758 |
| Pseudo $R^2$ | 0.153 |

**Table 2**

Bias in rating adjustments before default relative to a matched sample

Table 2 provides average rating adjustments at three-month intervals over the two-year period prior to default for both default observations and EDF-year matched non-default observations. The dependent variable, *RatingAdjust*, is the estimated Moody's total rating adjustment. The variable of interest, $Default_{t+k}$, is an indicator variable equal to one if a firm defaults over $k$-year period relative to period $t$, and zero otherwise. The last two rows provide formal tests of the difference in average rating adjustments over one and two years prior to default, respectively. 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.

| | (1)<br>Default issuers<br>*RatingAdjust* | (2)<br>Non-default issuers<br>*RatingAdjust* | (3)<br>Difference |
|---|---|---|---|
| $Default_{t-3mo}$ | -2.137*** | -0.918*** | -1.219*** |
| | (-8.89) | (-4.13) | (-3.92) |
| $Default_{t-6mo}$ | -1.707*** | -0.906*** | -0.801*** |
| | (-7.31) | (-4.02) | (-2.69) |
| $Default_{t-9mo}$ | -1.410*** | -0.902*** | -0.508* |
| | (-6.32) | (-3.97) | (-1.73) |
| $Default_{t-12mo}$ | -1.426*** | -0.812*** | -0.613** |
| | (-6.49) | (-3.40) | (-2.07) |
| $Default_{t-15mo}$ | -1.449*** | -0.824*** | -0.625** |
| | (-6.70) | (-3.45) | (-2.09) |
| $Default_{t-18mo}$ | -1.379*** | -0.762*** | -0.617** |
| | (-6.41) | (-3.20) | (-2.06) |
| $Default_{t-21mo}$ | -1.230*** | -0.789*** | -0.441 |
| | (-5.97) | (-3.37) | (-1.52) |
| $Default_{t-24mo}$ | -1.234*** | -0.832*** | -0.402 |
| | (-5.86) | (-3.68) | (-1.38) |
| $F$-test: $Default_{t-3} = Default_{t-12}$ | 21.27*** | 0.95 | 9.80*** |
| $F$-test: $Default_{t-3} = Default_{t-24}$ | 27.37*** | 0.37 | 12.14*** |

**Table 3**

Accuracy of rating adjustments and EDF – Type I errors

Table 3 provides the results from a logit regression examining the relationship between between issuers' missed default events and estimated default frequencies. In columns (1) and (2), the dependent variables are indicators equal to one if the actual rating ($E_{TypeI,Actual}$) or the model-based quantitative ratings ($E_{TypeI,QuantRating}$) failed to predict an actual event of default for a bond issue, and zero otherwise, respectively. The primary variable of interest, $EDF$, is the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). The last row of the table provides a formal test of the difference in the $EDF$ coefficient estimates for the actual and model-based quantitative ratings in columns (1) and (2), respectively. See the Appendix 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.

| | (1) | (2) |
|---|---|---|
| | $E_{TypeI,Actual}$ | $E_{TypeI,QuantRating}$ |
| $EDF$ | -35.2211*** | -1.8989 |
| | (-3.02) | (-0.49) |
| $Log(Assets)$ | 1.3822*** | 3.5568*** |
| | (5.25) | (2.99) |
| $IntCov$ | 0.0265 | 0.2860* |
| | (0.51) | (1.76) |
| $Debt/Equity$ | 0.0475 | 0.1146 |
| | (1.54) | (1.44) |
| $LargeLoss$ | 1.0370 | 2.1542 |
| | (1.11) | (1.18) |
| $NegRetain$ | -1.3394* | -1.4828 |
| | (-1.77) | (-1.27) |
| $Log(IssueAmt)$ | -0.0428 | -0.0716 |
| | (-0.41) | (-0.85) |
| $SeniorSecured$ | -0.1610 | -5.6802*** |
| | (-0.17) | (-2.62) |
| $Enhance$ | -1.8122*** | -0.1033 |
| | (-4.27) | (-0.15) |
| $Put$ | 0.9004 | -0.2506 |
| | (1.23) | (-0.43) |
| $Redeem$ | -0.9874** | 0.2074 |
| | (-2.52) | (0.37) |
| $Maturity$ | 0.0122 | -0.0047 |
| | (0.47) | (-0.19) |
| $GDP$ | 0.0002 | -0.0018*** |
| | (0.51) | (-3.96) |
| $CRSPBond$ | 5.9246 | -6.5161 |
| | (0.84) | (-1.16) |
| $S\&P500$ | -0.0001 | 0.0087* |
| | (-0.05) | (1.90) |
| $Log(Defaults)$ | -0.0028 | -0.0029 |
| | (-1.00) | (-0.91) |
| Constant | -14.5627*** | -17.0482** |
| | (-3.38) | (-2.43) |
| Observations | 3,336 | 3,336 |
| Pseudo $R^2$ | 0.885 | 0.659 |
| Area under ROC | 0.997 | 0.964 |
| $\chi^2$-Test: $EDF^{Actual} - EDF^{Quant}$ | 7.37*** | |

**Table 4**

Relevance of rating adjustments and EDF – Default recovery losses

Table 4 provides the results from an OLS regression of default recoveries on pre-default rating adjustments and the interaction of rating adjustments 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: $RatingAdjust$, the estimated Moody's total rating adjustment, and, $EDF$, the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). See the Appendix 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.

| | Rating at year $t-1$ | Rating at year $t-2$ |
|---|---|---|
| | (1) | (2) |
| | $DefaultPrice$ | $DefaultPrice$ |
| $RatingAdjust$ | 1.627** | 1.991*** |
| | (2.32) | (3.25) |
| $QuantRating$ | 2.017** | 2.940*** |
| | (2.14) | (3.45) |
| $EDF$ | -6.957 | -10.203 |
| | (-0.44) | (-0.33) |
| $RatingAdjust \times EDF$ | 1.236*** | 2.843** |
| | (2.76) | (2.03) |
| $QuantRating \times EDF$ | -0.071 | 3.012 |
| | (-0.02) | (0.60) |
| $Coupon$ | 0.327 | 0.411 |
| | (0.91) | (1.05) |
| $SeniorSecured$ | 22.709*** | 18.999*** |
| | (4.47) | (3.92) |
| $Subordinated$ | -2.975 | -1.405 |
| | (-0.63) | (-0.28) |
| $DistressedExchange$ | 29.294*** | 29.767*** |
| | (7.42) | (7.91) |
| $Chapter11$ | -5.889* | -8.149** |
| | (-1.90) | (-2.32) |
| $Equity$ | -4.062 | -4.290 |
| | (-0.55) | (-1.10) |
| $DefaultBarrier$ | -10.640 | -12.852 |
| | (-1.12) | (-0.98) |
| $LTDIssuance$ | -18.250*** | -9.749 |
| | (-2.90) | (-0.98) |
| $Profitability$ | -7.916 | 6.505 |
| | (-0.46) | (0.78) |
| $Intangibility$ | 1.447 | -3.270 |
| | (0.16) | (-0.37) |
| $Receivables$ | 11.739 | -8.840 |
| | (0.60) | (-0.53) |
| $Log(Assets)$ | -3.071 | -4.658** |
| | (-1.14) | (-1.99) |
| $Log(Employees)$ | 0.947 | 1.500 |
| | (0.57) | (0.85) |
| Industry Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Observations | 1,023 | 1,022 |
| Adjusted $R^2$ | 0.546 | 0.538 |

**Table 5**

Bias in Moody's rating adjustments within EDF deciles – All issuers

Table 5 provides average rating adjustments for decile portfolios based on market-implied default risk. The dependent variable, *RatingAdjust*, is the estimated Moody's total rating adjustment. The variable *EDF* is the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). The last row of the table provides a univariate means test of the difference in average rating adjustments for the decile 1 portfolio (the lowest expected default risk) and the decile 10 portfolio (the highest expected default risk). 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.

| | (1) *RatingAdjust* |
|---|---|
| *EDF* Decile=1 | 0.182* |
| | (1.84) |
| *EDF* Decile=2 | 0.210* |
| | (1.79) |
| *EDF* Decile=3 | -0.035 |
| | (-0.34) |
| *EDF* Decile=4 | -0.136 |
| | (-1.41) |
| *EDF* Decile=5 | -0.307*** |
| | (-3.34) |
| *EDF* Decile=6 | -0.359*** |
| | (-4.13) |
| *EDF* Decile=7 | -0.570*** |
| | (-6.80) |
| *EDF* Decile=8 | -0.463*** |
| | (-5.23) |
| *EDF* Decile=9 | -0.626*** |
| | (-6.53) |
| *EDF* Decile=10 | -0.792*** |
| | (-6.77) |
| Observations | 19,546 |
| *F*-Test: *EDF* Decile 1= *EDF* Decile 10 | 44.56*** |

**Table 6**

Accuracy of rating adjustments and EDF – Type II errors

Table 6 provides the results from a logit regression examining the relationship between between issuers' estimated false default predictions and default frequencies. In columns (1) and (2), the dependent variables are indicators equal to one if the actual rating ($E_{TypeII,Actual}$) or the model-based quantitative ratings ($E_{TypeII,QuantRating}$) falsely predicted default for a bond issue, and zero otherwise, respectively. The primary variable of interest, $EDF$, is the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). The last row of the table provides a formal test of the difference in the $EDF$ coefficient estimates for the actual and model-based quantitative ratings in columns (1) and (2), respectively. See the Appendix 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.

| | (1) $E_{TypeII,Actual}$ | (2) $E_{TypeII,QuantRating}$ |
|---|---|---|
| $EDF$ | 0.9207 | 6.7627*** |
| | (1.20) | (4.54) |
| $Log(Assets)$ | -0.8864*** | -1.5513*** |
| | (-13.38) | (-4.28) |
| $IntCov$ | -0.0645*** | -0.1811*** |
| | (-3.56) | (-8.65) |
| $Debt/Equity$ | -0.0088 | 0.1847*** |
| | (-0.76) | (3.66) |
| $LargeLoss$ | -1.9578*** | -0.9913 |
| | (-3.26) | (-1.17) |
| $NegRetain$ | 2.2708*** | -0.0263 |
| | (5.54) | (-0.10) |
| $Log(IssueAmt)$ | -0.2117* | 0.0345 |
| | (-1.72) | (0.93) |
| $SeniorSecured$ | -0.9445*** | -0.1022 |
| | (-3.01) | (-0.46) |
| $Enhance$ | 1.3372*** | 0.2933** |
| | (7.40) | (2.42) |
| $Put$ | -0.3023 | -0.0742 |
| | (-1.25) | (-0.44) |
| $Redeem$ | 1.6390*** | 0.2068 |
| | (8.86) | (1.61) |
| $Maturity$ | -0.0516*** | -0.0218*** |
| | (-5.22) | (-4.39) |
| $GDP$ | 0.0003*** | 0.0009*** |
| | (3.94) | (7.12) |
| $CRSPBond$ | -0.3155 | -2.0284** |
| | (-1.21) | (-2.13) |
| $S\&P500$ | -0.0003 | -0.0017*** |
| | (-1.10) | (-3.12) |
| $Log(Defaults)$ | -0.0001 | 0.0004 |
| | (-1.01) | (0.52) |
| $Convertible$ | 0.4873 | 1.8097 |
| | (0.57) | (1.50) |
| Constant | 3.6832*** | 3.5524 |
| | (3.86) | (1.45) |
| Observations | 300,947 | 300,947 |
| Pseudo $R^2$ | 0.485 | 0.502 |
| Area under ROC | 0.927 | 0.926 |
| $\chi^2$-Test: $EDF^{Actual} - EDF^{Quant}$ | 12.17*** | |

## Table 7

Relevance of rating adjustments and EDF – Issuer default prediction

Table 7 provides the results from a logit regression of future issuer default on rating adjustments and the interaction of rating adjustments with issuer risk of default. The dependent variable, $Default_{t+k}$, is an indicator variable equal to one if a firm defaults over $k$-year period relative to period $t$, and zero otherwise. The variables of interest include: *RatingAdjust*, the estimated Moody's total rating adjustment, and, $EDF$, the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). See the Appendix 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.

| | (1) $Default_{t+1}$ | (2) $Default_{t+3}$ |
|---|---|---|
| *RatingAdjust* | -0.0142*** | -0.0171*** |
| | (-7.56) | (-8.62) |
| *QuantRating* | -0.0095*** | -0.0096*** |
| | (-4.89) | (-4.71) |
| $EDF$ | -0.0975 | -0.0971 |
| | (-0.74) | (-0.75) |
| *RatingAdjust* $\times$ $EDF$ | -0.1021*** | -0.1238*** |
| | (-5.54) | (-6.48) |
| *QuantRating* $\times$ $EDF$ | -0.0220 | 0.0197 |
| | (-0.97) | (0.88) |
| $Log(Sales)$ | 0.0051 | -0.0007 |
| | (0.75) | (-0.10) |
| $Log(Assets)$ | 0.0049 | 0.0065 |
| | (0.83) | (1.00) |
| $Cash/Assets$ | 0.1413 | 0.1125 |
| | (1.31) | (0.98) |
| $(Cash/Assets)^2$ | -0.3992 | -0.3062 |
| | (-1.59) | (-1.13) |
| $EBITDA/Sales$ | 0.0018 | -0.0510 |
| | (0.08) | (-1.58) |
| $(EBITDA/Sales)^2$ | -0.0873* | -0.0602 |
| | (-1.94) | (-1.10) |
| $OperCF/Sales$ | 0.0121 | -0.0479 |
| | (0.47) | (-1.41) |
| $(OperCF/Sales)^2$ | 0.0049 | 0.0792 |
| | (0.13) | (1.63) |
| $IntExp/EBITDA$ | 0.0000 | 0.0000 |
| | (0.23) | (0.02) |
| $(IntExp/EBITDA)^2$ | 0.0000 | 0.0000 |
| | (0.65) | (0.89) |
| $Debt/Assets$ | 0.0079 | 0.0395 |
| | (0.12) | (0.55) |
| $(Debt/Assets)^2$ | 0.0790 | 0.0966 |
| | (1.08) | (1.22) |
| Constant | -0.0562 | -0.0109 |
| | (-1.35) | (-0.25) |
| Observations | 18,689 | 18,689 |
| Adjusted $R^2$ | 0.063 | 0.090 |

**Table 8**

Relevance of rating adjustments and EDF – Initial offering yields

Table 8 provides the results from an OLS regression of offering yields on rating adjustments and the interaction of rating adjustments with issuer risk of default. The dependent variable, $YSpread$, is the initial offering yield on a debt instrument. The variables of interest include: $RatingAdjust$, the estimated Moody's total rating adjustment, and, $EDF$, the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). See the Appendix 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.

| | (1)<br>$YSpread$ |
|---|---|
| $RatingAdjust$ | -31.7600$^{***}$ |
| | (-30.22) |
| $QuantRating$ | -40.1541$^{***}$ |
| | (-26.90) |
| $EDF$ | 203.1217$^{**}$ |
| | (2.17) |
| $RatingAdjust \times EDF$ | -115.2663$^{***}$ |
| | (-5.78) |
| $QuantRating \times EDF$ | -14.7049$^{*}$ |
| | (-1.87) |
| $Debt/Equity$ | -17.0757 |
| | (-0.91) |
| $IntCov$ | 0.6404$^{***}$ |
| | (4.29) |
| $Profit$ | -8.3069 |
| | (-0.46) |
| $Log(Assets)$ | 15.1733$^{***}$ |
| | (3.91) |
| $Log(IssueAmt)$ | 6.8486 |
| | (1.58) |
| $Maturity$ | 0.5165$^{***}$ |
| | (3.37) |
| $Senior$ | -8.9742 |
| | (-1.03) |
| $Secured$ | 50.7280$^{***}$ |
| | (3.71) |
| Year Fixed Effects | Yes |
| Observations | 7,199 |
| Adjusted $R^2$ | 0.693 |

**Table 9**

Relevance of rating adjustments and EDF – Equity market reaction to rating changes

Table 9 provides the results from an OLS regression of 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: $RatingAdjustIndicator$, an indicator variable equal to one if a firms' rating change consists of only a change in an issuer's qualitative credit rating (i.e., $PredictedRating$ remains the same), and zero otherwise, and $EDF$, the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). See the Appendix 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.

| | Downgrades (1) $CAR_{-1,+1}$ | Upgrades (2) $CAR_{-1,+1}$ |
|---|---|---|
| $RatingAdjustIndicator$ | -0.0172*** | 0.0033 |
| | (-3.60) | (0.67) |
| $EDF$ | -0.0716** | 0.0378 |
| | (-2.27) | (0.90) |
| $RatingAdjustIndicator \times EDF$ | -0.1791*** | 0.0598 |
| | (-3.14) | (0.68) |
| $RChange$ | -0.0230*** | 0.0001 |
| | (-5.93) | (0.03) |
| $IGrade$ | -0.0112 | 0.0012 |
| | (-1.14) | (0.33) |
| $Days$ | 0.0040** | -0.0009 |
| | (2.08) | (-0.76) |
| Constant | -0.0374*** | 0.0106 |
| | (-2.79) | (1.24) |
| Observations | 7,778 | 4,798 |
| Adjusted $R^2$ | 0.057 | 0.004 |

## Table 10

Additional analysis: Reputation and rating properties – Defaulting issuers

Table 10 presents the results from additional analyses on the importance of credit rating agency reputation concerns on ratings properties for the sample of defaulted firms. We use two different measures for reputation concerns following Becker and Milbourn (2011) and deHaan (2017), respectively, that are interacted with our variables of interest: *FitchMktSh*, the proportion of new bond ratings issued by Fitch in year $t$ for firm *i's* two-digit NAICS industry and *PostCrisis*, an indicator variable equal to one for the post-July 2009 period, and zero otherwise. The variable *FitchMktSh* is multiplied by -1 to allow for consistent interpretations of increased reputation concerns. Panel A provides average rating adjustments at three-month intervals over the two-year period prior to default for default observations. The dependent variable, *RatingAdjust*, is the estimated Moody's total rating adjustment. The variable of interest, $Default_{t+k}$, is an indicator variable equal to one if a firm defaults over $k$-year period relative to period $t$, and zero otherwise. The last two rows provide formal tests of the difference in average rating adjustments over one and two years prior to default, respectively. Panel B provides the results from a logit regression examining the relationship between between firms' estimated default frequencies and missed default events. In the first two columns and last two columns, the dependent variables are indicators equal to one if the actual rating ($E_{TypeI,Actual}$) or the model-based quantitative ratings ($E_{TypeI,QuantRating}$) failed to predict an actual event of default for a bond issue, and zero otherwise, respectively. The primary variable of interest, $EDF$, is the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). The last row of the panel provides a formal test of the difference in the $EDF$ coefficient estimates for the actual and model-based quantitative ratings. Panel C provides the results from an OLS regression of default recoveries on pre-default rating adjustments and the interaction of rating adjustments 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 *RatingAdjust* and $EDF$. See the Appendix 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.

*Panel A: Bias in rating adjustments before default*

| | $Reputation = -1 \times FitchMktSh$ | $Reputation = PostCrisis$ |
|---|---|---|
| | *RatingAdjust* | *RatingAdjust* |
| | (1) | (2) |
| $Default_{t-3mo}$ | -1.612*** | -1.812*** |
| | (-5.88) | (-10.14) |
| $Default_{t-6mo}$ | -1.281*** | -1.421*** |
| | (-4.72) | (-7.89) |
| $Default_{t-9mo}$ | -0.875*** | -1.158*** |
| | (-3.40) | (-6.54) |
| $Default_{t-12mo}$ | -0.839*** | -1.105*** |
| | (-3.17) | (-6.29) |
| $Default_{t-15mo}$ | -0.878*** | -1.055*** |
| | (-3.44) | (-6.11) |
| $Default_{t-18mo}$ | -0.741*** | -0.972*** |
| | (-2.77) | (-5.50) |
| $Default_{t-21mo}$ | -0.530** | -0.885*** |
| | (-2.04) | (-5.11) |
| $Default_{t-24mo}$ | -0.504** | -0.863*** |
| | (-1.99) | (-5.06) |
| $Default_{t-3mo} \times Reputation$ | -3.039*** | -0.607*** |
| | (-6.22) | (-5.26) |
| $Default_{t-6mo} \times Reputation$ | -2.259*** | -0.734*** |
| | (-3.16) | (-6.28) |
| $Default_{t-9mo} \times Reputation$ | -2.030*** | -0.609*** |
| | (-3.81) | (-5.71) |
| $Default_{t-12mo} \times Reputation$ | -2.111*** | -0.505*** |
| | (-3.12) | (-4.54) |
| $Default_{t-15mo} \times Reputation$ | -1.945*** | -0.201*** |
| | (-3.45) | (-2.97) |
| $Default_{t-18mo} \times Reputation$ | -1.861*** | -0.085 |
| | (-3.84) | (-1.25) |

**Table 10, Panel A** (*continued*)

| | $Reputation = -1 \times FitchMktSh$ | $Reputation = PostCrisis$ |
|---|---|---|
| | $RatingAdjust$ | $RatingAdjust$ |
| $Default_{t-21mo} \times Reputation$ | -1.646*** | -0.210*** |
| | (-3.34) | (-2.93) |
| $Default_{t-24mo} \times Reputation$ | -2.916*** | -0.235*** |
| | (-5.85) | (-2.90) |
| Observations | 3,624 | 3,624 |
| Adjusted $R^2$ | 0.118 | 0.118 |
| $F$-test: $Default_{t-3} = Default_{t-12}$ | 15.34*** | 33.00*** |
| $F$-test: $Default_{t-3} = Default_{t-24}$ | 20.35*** | 44.71*** |

*Panel B: Accuracy of rating adjustments and EDF – Type I errors*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $E_{TypeI,Actual}$ | $E_{TypeI,QuantRating}$ | $E_{TypeI,Actual}$ | $E_{TypeI,QuantRating}$ |
| | $Reputation = -1 \times FitchMktSh$ | | $Reputation = PostCrisis$ | |
| $EDF$ | -55.4779*** | -0.9664 | -37.0009*** | -2.4687 |
| | (-3.84) | (-0.29) | (-3.33) | (-0.76) |
| $Reputation$ | -7.4412 | 0.9010 | -10.7840*** | 0.8343 |
| | (-0.93) | (0.26) | (-4.11) | (0.96) |
| $EDF \times Reputation$ | -303.0091*** | 22.1995 | -82.4166* | -5.2749 |
| | (-2.94) | (0.79) | (-1.75) | (-0.78) |
| Control variables | Yes | Yes | Yes | Yes |
| Observations | 3,336 | 3,336 | 3,336 | 3,336 |
| Pseudo $R^2$ | 0.890 | 0.660 | 0.909 | 0.660 |
| Area under ROC | 0.992 | 0.965 | 0.998 | 0.964 |
| $\chi^2$-Test: $EDF^{Actual} - EDF^{Quant}$ | 13.47*** | | 8.89*** | |

*Panel C: Relevance of rating adjustments and EDF – Default recovery losses*

| | $Reputation = -1 \times FitchMktSh$ | | $Reputation = PostCrisis$ | |
|---|---|---|---|---|
| | Rating $t-1$ | Rating $t-2$ | Rating $t-1$ | Rating $t-2$ |
| | (1) | (2) | (3) | (4) |
| | $DefaultPrice$ | $DefaultPrice$ | $DefaultPrice$ | $DefaultPrice$ |
| $RatingAdjust$ | 1.589*** | 1.155** | 1.555*** | 1.733*** |
| | (2.82) | (2.33) | (4.36) | (2.76) |
| $QuantRating$ | 1.247* | 2.028*** | 1.766*** | 2.505*** |
| | (1.79) | (3.38) | (3.85) | (2.90) |
| $EDF$ | -0.896 | 45.664 | -7.014 | 22.682 |
| | (-0.02) | (0.94) | (-0.45) | (0.96) |
| $RatingAdjust \times EDF$ | 12.213* | 5.947** | 8.717*** | 2.081** |
| | (1.83) | (2.24) | (2.95) | (2.35) |
| $QuantRating \times EDF$ | 6.959 | 8.149 | 0.949 | 2.250 |
| | (1.01) | (1.13) | (0.35) | (0.58) |
| $Reputation$ | 48.933 | -20.942 | -22.836 | -15.017 |
| | (0.83) | (-0.32) | (-1.10) | (-0.93) |
| $EDF \times Reputation$ | 16.761 | 197.338 | -45.116 | -14.669 |
| | (0.06) | (0.56) | (-0.35) | (-0.17) |
| $RatingAdjust \times Reputation$ | 20.470*** | 21.411** | 7.699** | 3.895* |
| | (2.63) | (2.33) | (2.15) | (1.88) |
| $QuantRating \times Reputation$ | -8.602 | -2.412 | 5.128 | 2.681 |
| | (-1.08) | (-0.32) | (1.42) | (1.64) |
| $RatingAdjust \times EDF \times Reputation$ | 90.154** | 44.104 | 53.612*** | 10.097 |
| | (2.05) | (0.86) | (2.60) | (0.56) |
| $QuantRating \times EDF \times Reputation$ | -49.712 | -37.381 | 20.544 | 7.770 |
| | (-1.02) | (-0.66) | (0.94) | (0.47) |
| Control variables | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |

**Table 10, Panel C** (*continued*)

| | $Reputation = -1 \times FitchMktSh$ | | $Reputation = PostCrisis$ | |
|---|---|---|---|---|
| | Rating $t-1$ | Rating $t-2$ | Rating $t-1$ | Rating $t-2$ |
| | (1) | (2) | (3) | (4) |
| | $DefaultPrice$ | $DefaultPrice$ | $DefaultPrice$ | $DefaultPrice$ |
| Observations | 1,023 | 1,022 | 1,023 | 1,022 |
| Adjusted $R^2$ | 0.562 | 0.553 | 0.553 | 0.547 |

**Table 11**

Additional analysis: Reputation and rating properties – All issuers

Table 11 presents the results from additional analyses on the importance of credit rating agency reputation concerns on ratings properties for the sample of all rated firms. We use two different measures for reputation concerns following Becker and Milbourn (2011) and deHaan (2017), respectively, that are interacted with our variables of interest: $FitchMktSh$, the proportion of new bond ratings issued by Fitch in year $t$ for firm *i's* two-digit NAICS industry and $PostCrisis$, an indicator variable equal to one for the post-July 2009 period, and zero otherwise. The variable $FitchMktSh$ is multiplied by -1 to allow for consistent interpretations of increased reputation concerns. Panel A provides average rating adjustments for decile portfolios based on market-implied default risk. The dependent variable, *RatingAdjust*, is the estimated Moody's total rating adjustment. The variable $EDF$ is the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). The last row of the table provides a univariate means test of the difference in average rating adjustments for the decile 1 portfolio (the lowest expected default risk) and the decile 10 portfolio (the highest expected default risk). Panel B provides the results from a logit regression examining the relationship between between firms' estimated default frequencies and false default predictions. In the first two columns and last two columns, the dependent variables are indicators equal to one if the actual rating ($E_{TypeII,Actual}$) or the model-based quantitative ratings ($E_{TypeII,QuantRating}$) falsely predicted default for a bond issue, and zero otherwise, respectively. The primary variable of interest, $EDF$, is the expected default frequency, the market-based credit measure from Hillegeist et al. (2004). The last row of the panel provides a formal test of the difference in the $EDF$ coefficient estimates for the actual and model-based quantitative ratings. Panel C provides the results from a logit regression of future issuer default on rating adjustments and the interaction of rating adjustments with issuer risk of default. The dependent variable, $Default_{t+k}$, is an indicator variable equal to one if a firm defaults over $k$-year period relative to period $t$, and zero otherwise. The variables of interest include *RatingAdjust* and $EDF$. Panel D provides the results from an OLS regression of offering yields on rating adjustments and the interaction of rating adjustments with issuer risk of default. The dependent variable, $YSpread$, is the initial offering yield on a debt instrument. The variables of interest include *RatingAdjust* and $EDF$. Panel E provides the results from an OLS regression of 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: $RatingAdjustIndicator$, an indicator variable equal to one if a firms' rating change consists of only a change in an issuer's qualitative credit rating (i.e., *PredictedRating* remains the same), and zero otherwise, and $EDF$. See the Appendix 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.

*Panel A: Bias in rating adjustments within EDF deciles*

| | *Reputation =* $-1 \times FitchMktSh$ | *Reputation =* $PostCrisis$ |
|---|---|---|
| | (1) | (2) |
| | *RatingAdj* | *RatingAdj* |
| $EDF$ Decile=1 | 0.390$^{***}$ | 0.101 |
| | (5.99) | (0.91) |
| $EDF$ Decile=2 | 0.129 | 0.309$^{**}$ |
| | (1.39) | (2.32) |
| $EDF$ Decile=3 | 0.049 | -0.085 |
| | (0.58) | (-0.70) |
| $EDF$ Decile=4 | 0.023 | -0.115 |
| | (0.32) | (-1.01) |
| $EDF$ Decile=5 | -0.217$^{***}$ | -0.333$^{***}$ |
| | (-3.22) | (-3.12) |
| $EDF$ Decile=6 | -0.258$^{***}$ | -0.375$^{***}$ |
| | (-3.82) | (-3.76) |
| $EDF$ Decile=7 | -0.370$^{***}$ | -0.518$^{***}$ |
| | (-5.93) | (-5.46) |
| $EDF$ Decile=8 | -0.269$^{***}$ | -0.470$^{***}$ |
| | (-3.75) | (-4.53) |
| $EDF$ Decile=9 | -0.319$^{***}$ | -0.654$^{***}$ |
| | (-3.66) | (-5.41) |
| $EDF$ Decile=10 | -0.934$^{***}$ | -0.862$^{***}$ |

**Table 11, Panel A** (*continued*)

| | *Reputation* = $-1 \times FitchMktSh$ | *Reputation* = *PostCrisis* |
|---|---|---|
| | (1) | (2) |
| | *RatingAdj* | *RatingAdj* |
| | (-8.06) | (-5.90) |
| *EDF* Decile=1 × *Reputation* | -1.433*** | 0.225* |
| | (-4.06) | (1.91) |
| *EDF* Decile=2 × *Reputation* | 0.571 | -0.370* |
| | (1.05) | (-1.93) |
| *EDF* Decile=3 × *Reputation* | -0.629 | 0.168 |
| | (-1.21) | (1.05) |
| *EDF* Decile=4 × *Reputation* | -1.145*** | -0.076 |
| | (-2.72) | (-0.52) |
| *EDF* Decile=5 × *Reputation* | -0.664 | 0.084 |
| | (-1.58) | (0.57) |
| *EDF* Decile=6 × *Reputation* | -0.745* | -0.151 |
| | (-1.79) | (-1.11) |
| *EDF* Decile=7 × *Reputation* | -1.514*** | -0.490*** |
| | (-3.87) | (-3.59) |
| *EDF* Decile=8 × *Reputation* | -1.483*** | -0.443*** |
| | (-3.19) | (-2.92) |
| *EDF* Decile=9 × *Reputation* | -2.333*** | -0.449*** |
| | (-4.46) | (-2.75) |
| *EDF* Decile=10 × *Reputation* | -3.178*** | -0.655*** |
| | (-4.68) | (-3.52) |
| Observations | 19,546 | 19,546 |
| Adjusted $R^2$ | 0.026 | 0.025 |
| *F*-Test: *EDF* Decile 1= *EDF* Decile 10 | 99.29*** | 31.04*** |

*Panel B: Accuracy of rating adjustments and EDF – Type II errors*

| | *Reputation* = $-1 \times FitchMktSh$ | | *Reputation* = *PostCrisis* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $E_{TypeII,Actual}$ | $E_{TypeII,QuantRating}$ | $E_{TypeII,Actual}$ | $E_{TypeII,QuantRating}$ |
| *EDF* | 1.5221* | 9.5275*** | 0.8591 | 4.0837*** |
| | (1.67) | (7.07) | (1.01) | (2.95) |
| *Reputation* | 0.4647 | -0.8625 | 0.0111 | 0.2590 |
| | (0.34) | (-0.36) | (0.12) | (0.55) |
| *EDF* × *Reputation* | -17.9781** | 3.6363 | -2.7158** | 5.9733 |
| | (-2.37) | (0.32) | (-2.38) | (0.68) |
| Control variables | Yes | Yes | Yes | Yes |
| Observations | 300,947 | 300,947 | 300,947 | 300,947 |
| Pseudo $R^2$ | 0.485 | 0.503 | 0.485 | 0.504 |
| Area under ROC | 0.927 | 0.927 | 0.927 | 0.927 |
| $\chi^2$-Test: $EDF^{Actual} - EDF^{Quant}$ | 24.20*** | | 3.94** | |

*Panel C: Relevance of rating adjustments and EDF – Issuer default prediction*

| | *Reputation* = $-1 \times FitchMktSh$ | | *Reputation* = *PostCrisis* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Default_{t+1}$ | $Default_{t+3}$ | $Default_{t+1}$ | $Default_{t+3}$ |
| *RatingAdjust* | -0.0107*** | -0.0141*** | -0.0114*** | -0.0150*** |
| | (-3.65) | (-4.57) | (-6.56) | (-8.04) |
| *QuantRating* | -0.0085*** | -0.0095*** | -0.0068*** | -0.0080*** |
| | (-2.93) | (-3.25) | (-3.27) | (-3.70) |
| *EDF* | 0.0661 | 0.1742 | -0.0003 | 0.0203 |
| | (0.18) | (0.55) | (-0.00) | (0.13) |
| *RatingAdjust* × *EDF* | -0.1494*** | -0.1578*** | -0.1171*** | -0.1317*** |

**Table 11, Panel C** (*continued*)

| | $Reputation = -1 \times FitchMktSh$ | | $Reputation = PostCrisis$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $Default_{t+1}$ | $Default_{t+3}$ | $Default_{t+1}$ | $Default_{t+3}$ |
| | (-3.75) | (-3.93) | (-5.85) | (-6.43) |
| $QuantRating \times EDF$ | -0.0246 | 0.0174 | -0.0231 | -0.0183 |
| | (-0.44) | (0.35) | (-0.84) | (-0.69) |
| $Reputation$ | -0.0345 | 0.0023 | $0.0158^{***}$ | 0.0079 |
| | (-0.67) | (0.04) | (2.72) | (1.29) |
| $EDF \times Reputation$ | 0.9372 | 1.4624 | -0.2436 | $-0.3493^{**}$ |
| | (0.66) | (1.14) | (-1.40) | (-1.98) |
| $RatingAdjust \times Reputation$ | 0.0235 | 0.0188 | $-0.0084^{**}$ | $-0.0060^{*}$ |
| | (1.21) | (0.94) | (-2.49) | (-1.75) |
| $QuantRating \times Reputation$ | 0.0039 | -0.0015 | -0.0028 | -0.0003 |
| | (0.31) | (-0.11) | (-1.49) | (-0.13) |
| $RatingAdjust \times EDF \times Reputation$ | $-0.3422^{**}$ | $-0.2804^{**}$ | $-0.0875^{***}$ | $-0.0560^{**}$ |
| | (-2.06) | (-2.41) | (-3.02) | (-2.26) |
| $QualAdjust \times EDF \times Reputation$ | -0.0787 | 0.0080 | 0.0345 | -0.0017 |
| | (-0.34) | (0.04) | (1.13) | (-0.05) |
| Control variables | Yes | Yes | Yes | Yes |
| Observations | 18,689 | 18,689 | 18,689 | 18,689 |
| Adjusted $R^2$ | 0.066 | 0.093 | 0.070 | 0.093 |

*Panel D: Relevance of rating adjustments and EDF – Initial offering yields*

| | $Reputation = -1 \times FitchMktSh$ | $Reputation = PostCrisis$ |
|---|---|---|
| | (1) | (2) |
| | $YSpread$ | $YSpread$ |
| $RatingAdjust$ | $-31.4369^{***}$ | $-28.6022^{***}$ |
| | (-30.43) | (-23.70) |
| $QuantRating$ | $-40.8775^{***}$ | $-37.0200^{***}$ |
| | (-28.22) | (-22.63) |
| $EDF$ | $492.4320^{**}$ | $188.3690^{*}$ |
| | (2.45) | (1.74) |
| $RatingAdjust \times EDF$ | $-463.7653^{***}$ | $-218.7365^{***}$ |
| | (-13.74) | (-9.68) |
| $QuantRating \times EDF$ | -3.0472 | $-17.4932^{*}$ |
| | (-0.21) | (-1.81) |
| $Reputation$ | 26.6144 | $-54.2270^{**}$ |
| | (0.81) | (-2.39) |
| $EDF \times Reputation$ | $3660.4346^{*}$ | 77.3927 |
| | (1.90) | (0.47) |
| $RatingAdjust \times Reputation$ | $-38.4388^{***}$ | $-8.3865^{***}$ |
| | (-3.58) | (-4.01) |
| $QuantRating \times Reputation$ | $-37.8475^{***}$ | $-10.8179^{***}$ |
| | (-3.83) | (-6.43) |
| $RatingAdjust \times EDF \times Reputation$ | $-871.3274^{***}$ | $-50.9336^{*}$ |
| | (-3.03) | (-1.87) |
| $QuantRating \times EDF \times Reputation$ | 304.5432 | 23.5205 |
| | (1.17) | (0.89) |
| Control variables | Yes | Yes |
| Observations | 7,199 | 7,199 |
| Adjusted $R^2$ | 0.696 | 0.702 |

*Panel E: Relevance of rating adjustments and EDF – Equity market reaction to rating changes*

| | $Reputation = -1 \times FitchMktSh$ | | $Reputation = PostCrisis$ | |
|---|---|---|---|---|
| | (1) Downgrades $CAR_{-1,+1}$ | (2) Upgrades $CAR_{-1,+1}$ | (3) Downgrades $CAR_{-1,+1}$ | (4) Upgrades $CAR_{-1,+1}$ |
| $RatingAdjustIndicator$ | -0.0124*** | 0.0078** | -0.0246*** | 0.0101 |
| | (-2.74) | (2.09) | (-3.45) | (1.48) |
| $EDF$ | -0.0659** | 0.0402 | -0.0649* | 0.0356 |
| | (-2.41) | (1.24) | (-1.67) | (0.76) |
| $RatingAdjustIndicator \times EDF$ | -0.3143*** | 0.1509*** | -0.7494*** | 0.1724 |
| | (-7.76) | (2.60) | (-6.95) | (1.41) |
| $Reputation$ | -0.0148 | 0.0320 | -0.0053 | 0.0001 |
| | (-0.50) | (1.56) | (-1.08) | (0.02) |
| $RatingAdjustIndicator \times Reputation$ | -0.0660 | 0.0864*** | -0.0073 | 0.0086 |
| | (-1.05) | (2.70) | (-0.76) | (0.92) |
| $EDF \times Reputation$ | 0.1040 | 0.6397*** | -0.0291 | 0.0048 |
| | (0.32) | (3.13) | (-0.63) | (0.06) |
| $RatingAdjustIndicator \times EDF \times Reputation$ | -1.7277** | 1.9197*** | -0.1903 | 0.1295 |
| | (-2.18) | (4.73) | (-1.64) | (0.79) |
| Control variables | Yes | Yes | Yes | Yes |
| Observations | 7,778 | 4,798 | 7,778 | 4,798 |
| Adjusted $R^2$ | 0.063 | 0.021 | 0.060 | 0.005 |