Credit Rating Adjustments Prior to Default and Recovery Rates*

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Abstract

This study investigates whether rating agencies apply more stringent rating adjustments leading up to issuer defaults and whether the adjustments predict lender recoveries following default. Over the two years preceding default, we find that assigned ratings grow increasingly pessimistic relative to a standard benchmark rating model prediction, suggesting that rating agencies attempt to limit their reputational risk for defaulting issuers. In addition, we find that lender recovery rates are associated with both model-based predicted ratings and rating adjustments. Further, consistent with rating agencies making adjustments strategically, we find that rating adjustments are relatively more optimistic and less accurate measures of recovery rates when there is heightened competition from Fitch Ratings.

Keywords: credit rating agencies; rating stringency; loss given default; expected ratings

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 (Beaver et al., 2006; Cheng and Neamtiu, 2009; Cornaggia and Cornaggia, 2013). 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 borrowers, creditors, and investors. Recent empirical evidence supports these concerns (e.g., Cornaggia and Cornaggia, 2013).

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; Securities and Commission, 2003; Senate, 2002). Academic research supports 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 their ratings. This can reduce future demand for their services, and thus future economic rents. Recent empirical evidence furthers this notion as deHaan (2016) shows that market participants reduced their reliance on corporate credit ratings after the 2008 financial crisis, even though corporate rating quality did not suffer in the pre-period.[1] However, Bolton et al. (2012) also shows that ratings inflation is expected to be more common when the risk of detection is lower.

[1]The Big Three have also suffered from a more stringent regulatory framework as The Dodd-Frank Wall Street Reform and Consumer Protection Act calls for a reduction in regulatory reliance on firms' assigned credit ratings.

Prior empirical evidence provides support for the effect of reputational costs on credit rating properties in the settings of mortgage-backed securities ratings prior to the collapse of the market (Ashcraft et al., 2011), of ratings-based contracts (Kraft, 2015a), of widely-covered issuers (Bonsall et al., 2016a), and of bank securitization (Bonsall et al., 2015b).

In this study, we examine the impact of issuer default on credit rating agencies' strategic use of ratings adjustments. Certain rating agencies (i.e., Moody's and Fitch) rely on both quantitative and qualitative analyses to forecast both the incidence of default and loss given default.[2] As Moody's discusses, "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, 2016a). We examine whether these subjective rating adjustments are applied strategically to limit potential reputational harm from being optimistic at the time of issuer default. That is, we investigate whether rating adjustments are increasingly pessimistic (i.e., stringent) as default approaches, consistent with the adjustments being strategically biased. In addition, we examine if rating adjustments are useful in explaining default recoveries. Further, we examine whether these actions are less pronounced when rating agencies face weaker incentives to protect their reputations.

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). We define the adjustments as optimistic (pessimistic) when the actual rating is more (less) favorable than the predicted rating from the benchmark model estimated for that year. These rating adjustments are comprised of both hard and soft adjustments. Hard adjustments are quantitative-based and typically made to recast financial ratios based on reported GAAP numbers to amounts more appropriate for judging credit risk, such as the

[2]While S&P also relies on both quantitative and qualitative analysis, S&P's assigned ratings do not incorporate loss given default. Given this, Moody's ratings are the focus of our study.

capitalization of operating leases to assess an issuer's leverage. Conversely, soft adjustments are qualitative in nature and typically include items that require greater judgement, such as managerial ability (Bonsall et al., 2015a), governance, and internal controls, among others.

As discussed in prior research (Bonsall, 2014; Bonsall et al., 2016b; Griffin and Sanvicente, 1982; Jorion et al., 2005; Kliger and Sarig, 2000; Walker, 2010), the issuer-pay model can lead to rating adjustments that incorporate issuers' private information. Specifically, privileged internal data (e.g., budgetary information or management forecasts) can be given to rating agencies without fear that the specific information will be revealed through the public release of credit ratings. While certain private information may be more quantitative in nature, private information can also be qualitative. For instance, access to management can allow credit rating agencies to more adequately assess management characteristics like ability and integrity and firm characteristics like competitiveness within an industry or business segment and corporate culture, among others.[3] Therefore, these adjustments can be warranted because alterations to GAAP-based financial ratios and qualitative information about attributes like management quality can plausibly provide incremental information regarding firms' ability to meet debt service obligations beyond that provided by a financial ratio-based model. However, these adjustments can also provide a means for inflating ratings because of the inherently subjective nature of evaluating qualitative information.

Using Moody's Default and Recovery Database for default dates and losses and Moody's ratings from 1992–2015, we find that qualitative adjustments become increasingly pessimistic leading up to events of default. The increase in pessimism 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 Moody's rating scale). We also examine a matched sample of issuers from the same industry and year but do not default within the next five years.

[3]While firm-provided nonpublic information could assist rating agencies in conducting qualitative analysis, it is not a necessity. For instance, sell-side equity analysts conduct qualitative analysis despite Regulation Fair Disclosure eliminating their access to material nonpublic information (Bradley et al., 2016; Brown et al., 2015; Cheng et al., 2016).

These non-defaulting issuers allow us to control for any potential industry and year effects that could influence our findings. While we find evidence of ratings pessimism with non-defaulting firms, the magnitude is much smaller and does not appear to follow the time trend observed for defaulting issuers over the same two-year period of time. The difference in rating adjustments for default and non-default firms continues to provide evidence of increasing pessimism for default firms of similar magnitude.

The importance of rating accuracy also extends to creditor recovery rates. Recovery rates are important for rating users because they assist investors in determining how much collateral will be recovered during liquidation. This is particularly difficult as it requires extensive judgement about the interplay among capital structure, creditor rights, jurisdiction, state law, and other forces in determining liquidation payouts. Therefore, inaccurate assessments of creditor recovery rates could significantly reduce the informativeness of Moody's assigned credit ratings. We posit that reputational concerns extend to Moody's estimation of creditor recovery rates; thus we predict a positive relation between rating agency adjustments and creditor recovery rates. We find that rating adjustments for defaulting issuers are predictive of recovery rates—i.e., optimistic adjustments predict lower losses given default.

Our findings suggest that Moody's cares more about its reputation as firms' default risk increases and that Moody's assigns less optimistically biased credit ratings for firms that eventually default. However, the possibility exists that firms approaching default either voluntarily or at the rating agencies' requests provide credit rating agencies with more information to accurately assess 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 cannot 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. If true, our primary findings could be the result of greater information sharing by issuers prior to default rather than credit rating agencies' reputational concerns.

To better assess the role that reputational concerns play in the rating process, we examine whether increased competition from other credit rating agencies impacts the quality of incumbents' assigned credit ratings. Specifically, we examine whether Moody's rating adjustments are more optimistic leading up to default and less predictive of creditor recovery rates when Fitch has greater market share in a given industry. Variation in rating agency competition provides a potentially powerful setting to examine reputational concerns as Becker and Milbourn (2011) show that the dominant credit rating agencies (i.e., Moody's and S&P) provide lower quality ratings when competition via Fitch's coverage of new issuers in an industry is greater. Such behavior by the incumbent rating agencies is consistent with trading off reputation against lower future economic rents. Consequently, we posit that if reputational concerns are the main driver of our primary findings, then heightened competition among credit rating agencies may reduce incumbent rating agencies' willingness to assign less optimistic and more accurate ratings. Conversely, we would not expect a similar effect if our primary findings were the result of greater information sharing by firms that eventually default. We find results consistent with the former; thus our primary findings do not appear to be influenced by greater information pre-default.

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. In addition, Donovan et al. (2015) suggests accounting conservatism impacts creditor recovery rates. In supplemental analysis, we control for accounting conservatism and find that our inferences related to recovery rates are unchanged.

Our setting allows us to extend various streams of prior research. For instance, because default events are relatively rare, firms approaching default are likely monitored by various market participants such as investors, competitors, regulators, media, among others. This suggests that the reputational penalties for failing to provide accurate and reliable credit ratings for firms approaching default could be particularly severe. However, prior research highlights multiple instances where credit rating agencies use credit rating adjustments opportunistically and thus fail to accurately assess issuers' overall credit risk. These instances include ratings for collateralized debt obligations (Griffin and Tang, 2012), when loan contracts contain performance-pricing provisions (Kraft, 2015a), among others. We extend prior research by documenting that catering incentives under the issuer-pay compensation model can be mitigated when the tension between rating users and issuers for accurate versus inflated ratings, respectively, is arguably the greatest (i.e.,when firms approach default); thus, we highlight when rating adjustments are used defensively by rating agencies.

Our study also has implications for the scant literature that addresses rating agency monitoring, as well as the literature that examines the role of heightened competition on the actions of rating agencies. For instance, Bonsall et al. (2015b) suggest 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 extend this line of research by highlighting that heightened competition can result in less effective rating agency monitoring even during periods when heightened market participant awareness is likely significant.

In the same vein, prior research suggests that heightened competition can cause credit rating agencies to reduce the quality of their ratings across various asset classes (Becker and Milbourn, 2011; Bolton et al., 2012; Bonsall et al., 2016a; Griffin et al., 2013).[4] Conversely, Xia (2014) suggests that initiation of rating coverage by Egan Jones Ratings Company results in improved rating quality by S&P. Because default prediction is one of the most important

[4]In addition, while certain studies examine the impact of Fitch's market share on incumbent rating agencies' ratings quality (Becker and Milbourn, 2011; Bonsall et al., 2016a), Kraft (2015a) examines the presence of Fitch rather than the market share of Fitch.

qualities of issuers' assigned credit ratings, our results extend prior research by highlighting that heightened competition causes credit rating agencies to allow their reputations to wane even in instances where inaccurate credit risk assessments may harm them the most. In addition, while prior research offers mixed evidence as to whether documented rating agency stringency over time impacts creditor recovery rates (Alp, 2013; Baghai et al., 2014), our study suggests that heightened rating agency competition reduces the impact that increased rating agency stringency can have on creditor recovery rates. In this regard, our findings suggest that market participants should use caution when employing creditor recovery rates in their analysis.

Finally, we contribute to the empirical literature examining the determinants of creditor recovery rates. Several studies suggest that industry affiliation and the economic health of an industry (Acharya et al., 2007; Altman and Kishore, 1996; Hanson and Schuermann, 2004; Shleifer and Vishny, 1992), default event type (Altman and Karlin, 2009), propensity for conservative accounting (Donovan et al., 2015), and a broad set of bond, firm, macroeconomic and liquidity characteristics (Jankowitsch et al., 2014) are important determinants of recovery rates. Our findings extend prior literature by providing evidence that subjective adjustments to model-based ratings are informative about recovery rates in default, and thus furthers our understanding of the importance of soft information during the rating process.

2 Background and research hypotheses

The reliance of the major rating agencies on issuer fees, rather than investor fees, has led to concerns that reported ratings are influenced by the interests of issuers. In particular, the issuer-pay model is often attributed to providing incentives for inflated ratings and delayed incorporation of unfavorable information into ratings about issuers' creditworthiness (e.g., White, 2010). Prior accounting and finance studies provide evidence consistent with such concerns. For instance, Jiang et al. (2012) shows that S&P assigned more favorable ratings after adopting issuer-pay, particularly for issuers that offered expected fees and were rated higher by Moody's, whom had previously adopted the issuer-pay model. Xia (2014) finds that the quality of S&P's ratings for an issuer improves when the Egan-Jones Rating Company, an investor-pay rating agency, initiates coverage. Cornaggia and Cornaggia (2013) provides evidence that Moody's ratings are more stable and have lower false positives and negatives but lack timeliness relative to RapidRatings, another investor-pay rating agency. These tendencies by S&P and Moody's to have lower quality corporate ratings relative to investor-paid rating agencies are consistent with conflicts created by the issuer-pay model. Additional evidence of issuer-pay conflicts is provided by Baghai and Becker (2016) who suggest a positive relation exists between non-rating fee revenue and assigned credit ratings, and by Efing and Hau (2015) who document that ratings are inflated for issuers that provide rating agencies with more securitization business. Lastly, Griffin and Tang (2012) suggest that rating agencies made unjustified adjustments to their rating models to assign more favorable credit ratings to collateralized debt obligations.

The major rating agencies indicate that the reputational harm that can arise from untimely or inaccurate ratings is sufficient to mitigate concerns over possible conflicts under the issuer-pay model (Moody's Investors Service, 2015; Standard & Poor's, 2015). The agencies also claim that their role as Nationally Recognized Statistical Ratings Organizations, or NRSROs, leads them to favor stable ratings over timely and accurate ratings, as rating reversals are costly to investors and other users of ratings. Prior research provides evidence that supports these claims. Bolton et al. (2012) demonstrates how the quality of ratings should vary with costs arising from reputational harm—e.g., ratings inflation should be less common when detection is more likely and lost profits arising from detection are higher. In addition, Bar-Isaac and Shapiro (2013) show that reputational harm concerns are more (less) likely to discipline the actions of credit rating agencies during economic busts (booms), as fee income is low (high) and expected defaults are high (low).

Because of the magnitude of losses that can occur from issuer default, bond issuers pay close attention to ratings both before and after default. This is done in an effort to assess the likelihood of default and expected losses ex ante, and to assess the accuracy of ratings issued by the major rating agencies ex post, respectively. For example, the annual default rate from 1983–2015 averaged 1.6 percent. In addition, average recovery rates ranged from 80.4 percent for loans to only 28.2 percent for subordinated bonds (Moody's Investors Service, 2016b). These amounts, however, can vary considerably over the business cycle, with defaults being more common and default recoveries being lower during periods of economic decline.

Given the importance of issuer defaults to investors, the major rating agencies proactively promote the accuracy of their ratings prior to default. Moody's publishes statistics annually regarding the discriminatory power of its ratings (Moody's Investors Service, 2016b). Commonly cited metrics by Moody's include the average letter ratings prior to default and the average default position (e.g., the percentage of issuers with higher or equal ratings as defaulting issuers). Likewise, Standard & Poor's reports annually the number of defaults separately by investment-grade and speculative-grade ratings, with the ratings being those in place as of January 1 in the year of default (Vazza and Kraemer, 2016). Based on Moody's statistics (Moody's Investors Service, 2016b), the average discriminatory power of ratings for default is relatively short-term (e.g., the last year or two) with limited, albeit some, warning over the long-term (e.g., over five years prior to default).

At issuance, it is difficult for investors to assess the quality of firms' assigned credit ratings with respect to ultimate default prediction as the risk of default over the long-term at this point in time is low. However, as both the risk of default grows and the risk of investors learning of inflated ratings looms larger over time, credit rating agencies may adjust their ratings accordingly. This is particularly relevant when one considers that credit rating agencies may become concerned over potential reduced demand for their ratings if users believe firms' assigned credit ratings are inaccurate. If credit rating agencies respond to these concerns, they may increasingly rely on their knowledge of issuers' creditworthiness by going beyond information conveyed by standard financial ratios. As discussed extensively in Kraft (2015b), the credit rating agencies commonly make hard and soft adjustments to arrive at their actual ratings. 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 the issuer management, governance, controls, and other internal and external factors that could affect the creditworthiness of the issuer.

Rating adjustments can be used opportunistically to inflate ratings (e.g., Kraft, 2015a) or to convey new information to financial markets (e.g., Jorion et al., 2005). We consider the difference between the actual rating and the predicted rating from a standard rating model to be comprised of both hard and soft adjustments. Given the increased reputational costs from overrating an issuer prior to default and the increased ability for investors to ex post assess the bias of credit ratings, we predict that rating agencies will go beyond standard rating models to issue ratings that are more pessimistic prior to default. Formally, we state this prediction as our first research hypothesis (in alternative form):

> ***Hypothesis 1 (H1): Credit rating agencies make rating adjustments to reduce rating optimism prior to issuer default.***

The credit rating agencies are judged not only on the bias in their ratings but also on their accuracy. In the context of issuer default, investors will judge whether certain rating agencies' assigned credit ratings provide information to predict loan recovery rates. With rating adjustments, more accurate ratings are those that allow market participants to discriminate across issuers regarding the magnitude of actual default amounts. Given the large differences in creditor recovery rates, this information should be of primary importance to investors. Similar to potential forgone future fees for rating agencies with inflated ratings prior to default, we expect that reputation costs will be higher for rating agencies with less accurate ratings of default recoveries. This prediction leads to our second research hypothesis:

> ***Hypothesis 2 (H2): Credit rating agencies' adjustments predict issuer default recovery rates.***

Critics of the major rating agencies suggest that credit ratings agencies are influenced by incentives inherent to the issuer-pay compensation model to provide issuers with more favorable credit ratings (Partnoy, 1999, 2006). Prior research supports this contention and shows that rating agencies offer favorable credit ratings to issuers in various instances (Baghai and Becker, 2016; Becker and Milbourn, 2011; Griffin and Tang, 2012; Kraft, 2015a). Defaulting issuers in our sample may face the greatest pressure to maintain favorable credit ratings from rating agencies. This could limit our ability to find results consistent with our hypotheses.

3 Sample and descriptives

3.1 Sample

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 21,357 observations representing 2,616 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.[5] We limit our analyses to default events for U.S. publicly traded industrial firms and default types identified as distressed exchanges,

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

Chapter 11 (re-organization) bankruptcy, and missed payments on interest or principal.

We match the default data with accounting data in the Compustat annual files using 6-digit CUSIP. To ensure reliable matches, we manually check all matches. In addition, default events not having a match based on CUSIP are matched by hand through a combination of manual review of firm names and year in Compustat point-in-time files as well as CapitalIQ firm identifier lookup. This process yields our base sample matched to a GVKEY in Compustat, before eliminating firm-years with missing values for controls, with 1,010 (1,156) default events associated with 2,976 (4,937) individual issues for 873 (949) firms during the period covering 1992 to 2015, representing individual issues with (without) default prices in the DRD.[6]

The final step in our sample selection process is to match the default data with predicted rating and rating optimism data generated from the estimation of our rating model based on the non-market inputs used in Baghai et al. (2014). We gather all inputs to the rating model from Compustat and estimate the rating model cross-sectionally by year. Matching the predicted ratings and rating optimism data, along with control variables, reduces our baseline recovery rate sample to 1,126 observations.

3.2 Descriptives

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 11.4, 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

[6]Default dates for issues without default prices can still be used in the analyses to examine changes in ratings as default approaches.

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 slightly over one percent of total assets. Rent expense averages between one and two 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.

Panel B of Table 1 presents descriptive statistics for the defaulted instruments and firm characteristics of the firms in our default sample during the period covering 1992–2015. The mean (median) creditor recovery rate (i.e., default price) in the sample is 41.04 (34.75) percent. The first quartile creditor recovery rate is 21.25 percent and the third quartile is 61.88 percent. These statistics indicate that creditor losses are very significant at borrower default, with losses of nearly 80 percent of the value of the outstanding debt claims at the 25th percentile. Turning to the ratings measures, the mean rating optimism in the sample is -2.51 and the mean expected ratings is 8.47. The mean optimism of -2.51 indicates that rating adjustments in the year prior to default are generally pessimistic relative to the quantitatively modeled rating during our sample period.[7] Senior secured debt instruments account for 7.3 percent and subordinated debt accounts for 6.6 percent of all debt instruments in the sample. Nearly half of the defaults events (49.3 percent) are Chapter 11 bankruptcy filings, 21.0 percent are a result of distressed exchanges, and the remainder are missed payments on interest or principal or both. Firms in the sample are fairly large with an average market capitalization in excess of $2.6 billion and mean total assets in excess of $3.2 billion in the year prior to default. The average ratio of long-term debt to total debt is 82.2 percent, suggesting that defaulting firms have relatively high long-term indebtedness, which is usually an indicator of stability.

Table 2 presents correlations for the variables in the sample. Rating optimism is positively correlated with default price, providing some initial evidence that rating optimism

[7]This mean optimism relates to the reduced sample used in the default recovery analysis and differs from the mean optimism of -1.002 in the average rating optimism prior to default analysis.

is informative of creditor recovery rates. Consistent with existing evidence, senior secured debt is positively correlated with default price (0.23). Similarly, distressed exchanges are positively correlated (0.33) whereas Chapter 11 bankruptcy is negatively correlated (-0.26) with default price. This evidence supports the notion that debt seniority and default event type are important determinants of creditor recovery rates; we control for these and other factors in the regression based analyses of creditor recovery rates.

4 Empirical results

4.1 Rating adjustments pre-default

To examine our first hypothesis we first estimate issuers' predicted credit ratings and the level of optimism rating agencies apply during the rating process. Our measure of the optimism in Moody's reported ratings is $Optimism = Rating - \widehat{Rating}$, where $\widehat{Rating}$ is the predicted rating (i.e., $PredictedRating$). $Optimism$ takes on positive values when actual ratings are higher than predicted ratings and negative values when actual ratings are lower than predicted ratings. We estimate predicted credit ratings 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. These factors lead to the following ordered probit model:

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

where $Rating$ is coded from 1 (C) to 21 (Aaa);[8] $IntCov$ is earnings before interest, taxes, depreciation, and amortization divided by interest expense; $Profit$ is earnings before interest, taxes, depreciation, and amortization divided by sales; $Book\_Lev$ is the sum of long- and short-term debt divided by total assets; $Size$ is the natural logarithm of total assets; $Debt/EBITDA$ is the sum of long- and short-term debt divided by earnings before interest, taxes, depreciation, and amortization, and is set equal to zero if $Debt/EBITDA < 0$; $Neg.Debt/EBITDA$ is an indicator variable equal to one if $Debt/EBITDA < 0$, and zero otherwise; Vol is the standard deviation of $Profit$ over the prior five fiscal years with a minimum of two years to be included in the sample; $Cash/Assets$ is cash and short-term investments divided by total assets; $ConvDe/Assets$ is convertible debt divided by total assets; $Rent/Assets$ is rent expense divided by total assets; $PPE/Assets$ is net property, plant, and equipment divided by total assets; and $CAPEX/Assets$ is capital expenditures divided by total assets. For purposes of our rating stringency analysis, we estimate equation (1) cross-sectionally by year to allow credit rating standards to vary through time. We also include industry fixed effects.

Table 3 presents the pooled regression estimates for equation (1). In this pooled estimation, we use robust standard errors clustered by firm. 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 expected as firms that are larger, more profitable, have more tangible assets, and less debt are typically considered more creditworthy.

4.1.1 Within-firm tests

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

[8] The coding is the opposite of Jankowitsch et al. (2014); hence the opposite prediction for ratings (i.e., positive rather than negative).

model or regulatory reliance on ratings may 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, our first hypothesis predicts that catering related rating optimism should decline as default nears. To test this prediction, we estimate the following OLS model:

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

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. We use robust standard errors clustered by firm in the estimation of equation (2). H1 advances that rating optimism will decline as default approaches. We test this over the one and two years prior to default—i.e., ϕ_1—ϕ_4<0 and ϕ_1—ϕ_8<0, respectively.

Panel A of Table 4 presents the results from the estimation of equation (2). We find that the average value for *Optimism* 24 months prior to default is -0.83 notches, providing evidence that the adjustments by Moody's are not optimistic but rather are pessimistic relative to the predicted rating provided by the estimation of equation (1). In addition, while rating optimism declines as the default date approaches as predicted by H1, we note that the largest magnitude changes in rating optimism occur in the one-year period prior to default. In fact, while the amount of rating pessimism increases by roughly 102 percent, or approximately 0.84 rating notches, from month $t-24$ through $t-3$, roughly 77 percent of this increase occurs in the one-year period leading up to default. As shown at the bottom of Table 4, these differences are statistically significant. Collectively, the evidence in Panel A of Table 4 suggests that in the two years prior to default, reputational concerns lead Moody's to reduce (increase) its rating optimism (pessimism) for future defaulting debt obligations, and that they do so early enough to signal to rating users that certain firms are approaching default.

4.1.2 Across-firm tests

To investigate whether the results presented in Panel A of Table 4 for equation (2) are indicative of a response to increasing reputational concerns in advance of default events or are merely symptomatic of industry or time trends, we create a control group of comparison firms that are in the same two-digit North American Industry Classification System (NAICS) industry and that have outstanding debt two years prior to the sample firm's default event but do not default within the following five years after the sample firm's default event date. This matching controls for industry and time-period differences in rating levels. We modify equation (2) to separate coefficients for $Default$ for default and non-default firms. We then take the difference between the coefficients for $Default$ for the two subgroups. The equation is estimated by omitting the intercept.

Panel B of Table 4 presents the results from estimating the modified version of equation (2). Because the sample is the same for the default firms the coefficient estimates in column (1) of Panel B mirror those in Panel A. For the matched non-default firms, we find in column (2) that their rating adjustments are also pessimistic at months $t-24$ through $t-3$. This suggests that either the years or industries of our sample firms lead to rating adjustments that are pessimistic. We find, however, that the pessimism in the rating adjustments is relatively unchanged over time. For instance, as displayed at the bottom of column (2), the changes in rating adjustments from month $t-12$ through $t-3$ and from month $t-24$ through $t-3$ are insignificant, respectively. In contrast, the changes in the differenced rating adjustments in column (3) grow increasing pessimistic leading up to default. Tests of the differences, shown at the bottom of the column, are statistically significant. These findings corroborate the evidence presented in Panel A that Moody's rating adjustments appear to respond to reputational concerns as defaults approach.

4.2 Rating adjustments and default recoveries

Over time credit rating agencies have faced scrutiny for failing to provide accurate assessments of credit risk. While prior research typically examines whether assigned credit ratings adequately reflect default risk at a point in time, rating users are also concerned with whether assigned ratings adequately reflect amounts to be recovered upon default. We examine recovery rates for specific default events as identified by the Moody's DRD: Chapter 11 liquidation and restructuring, distressed exchanges, and payment defaults.[9] For each event, we examine whether optimistic ratings, judged by the difference between the actual and expected rating six months prior to the default event, leads to greater creditor recovery. Similar to Jankowitsch et al. (2014), we examine the recovery rate for the default events using the following OLS regression model:

$$DefaultPrice_{it} = \delta_0 + \delta_1 PredictedRating + \delta_2 Optimism_{it} + \sum \lambda_j Control_{j,it} + \varepsilon_{it} \quad (3)$$

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. We expect that lower predicted credit ratings estimated prior to default events (i.e., indicative of worse issuer credit quality) are associated with lower recovery rates. Therefore, we expect that $\delta_1 > 0$. If rating adjustments provide information about loss recovery prior to default, then we predict $\delta_2 > 0$. However, if rating adjustments provide less of a warning about recovery amounts relative to predicted ratings, then we predict $\delta_2 < \delta_1$. We use robust standard errors in the estimation of equation (3). Control variables include the initial annual payment for a bond expressed as a percentage of the face amount ($Coupon$), an indicator variable equal to one if the debt instrument is senior and secured, and zero otherwise ($SeniorSecured$), an indicator variable equal to one if the debt instrument is subordinated, and zero otherwise ($Subordinated$), an

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

indicator variable equal to one if the default type is distressed exchange, and zero otherwise ($DistressedExchange$), an indicator variable equal to one if the default type is Chapter 11 bankruptcy, and zero otherwise ($Chapter11$), the market value of equity divided by total assets ($Equity$), an assessment of distance to default, measured as short-term debt plus one half long-term debt scaled by total assets ($DefaultBarrier$), the ratio of long-term debt to total debt ($LTDIssuance$), earnings before interest, taxes, depreciation, and amortization scaled by lagged total assets ($Profitability$), intangible assets divided by total assets ($Intangibility$), total receivables divided by total assets ($Receivables$), the natural logarithm of total assets ($Log(TotalAssets)$), and the natural logarithm of the number of firm employees ($Log(Employees)$).

Table 5 presents the results from estimating equation (3). Column (1) uses credit rating information at year $t-1$ relative to default and column (2) uses credit rating information at year $t-2$. In both columns, the coefficients on $PredictedRating$ ($\widehat{\delta_1}$) are positive and statistically significant at the 0.01 level ($t = 3.57$ and $t = 3.61$, respectively), consistent with more favorable predicted credit ratings leading to higher lender recoveries in bankruptcy. We also find that the coefficients on $Optimism$ ($\widehat{\delta_2}$) are positive and statistically significant at the 0.01 level ($t = 3.51$ and $t = 3.15$, respectively), consistent with rating adjustments providing incremental information about future recoveries from defaulted issuers. In terms of whether $Optimism$ is less effective at predicting recoveries relative to $PredictedRating$, we report an F-test of $\delta_1 = \delta_2$ at the bottom of Table 5. The null hypothesis is not rejected at the 0.05 level (two-sided) in both columns, suggesting that rating adjustments do not provide less information about default recoveries than predicted credit rating based on quantitive data for adjustments existing one and two years prior to default. This is somewhat surprising as rating adjustments are often viewed as the vehicle for rating agencies to build bias into their final ratings, which could diminish the ability of such adjustments to predict recovery given default. Overall, the results in Table 5 provide evidence consistent with H2 that rating agencies' adjustments predict default recoveries by creditors.

4.3 The effect of rating competition from Fitch

While our primary findings suggest that reputational concerns from failing to provide accurate ratings results in reduced rating optimism and greater recovery rate estimation, the possibility exists that default issuers provide rating agencies with greater information during the rating process. Specifically, firms that eventually default could either voluntarily or at the request of credit rating agencies provide credit rating agencies with more information during the rating process. This could result in more accurate credit risk assessments for these firms.

Issuers may engage in greater information sharing with credit rating agencies for multiple reasons. First, if issuers believe that default is 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 cannot only help determine the specific timing of default but also allow market participants to more accurately assess the remaining 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., 2016b), 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 perceived 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.[10] Other studies (Bonsall et al., 2016a; Dimitrov et al., 2015; Kedia et al., 2014) 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, the advent of greater rating agency competition provides us with a potentially powerful setting to distinguish between a reputation-based explanation and an information sharing explanation for the results in Tables 4 and 5. For defaulting issuers, we predict that greater rating competition from Fitch will cause Moody's and S&P to be less diligent in reducing the optimism in rating adjustments prior to default. In addition, we predict that credit rating adjustments will be less predictive of default recoveries. Alternatively, if firms were providing credit rating agencies with greater information during the rating process pre-default, then credit rating agencies could continue to be motivated to accurately assess issuers' default risk despite increased rating agency competition.[11]

We explore the influence of rating competition on our findings in two ways. First, we estimate a modified version of equation (2) that interacts each $Default$ indicator variable with $FitchMktSh$, defined as the proportion of new bond ratings issued by Fitch in year t for firm i's two-digit NAICS industry.[12] If reputational risk concerns are important determinants

[10]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.

[11]Credit rating agencies may also simply choose to ignore issuer-provided information leading up to default when competition increases.

[12]Main effects for $FitchMktSh$ are not included as the interaction of $Default$ with $FitchMktSh$ captures the four quarters for each year prior to default.

of our primary findings, we expect that the coefficient on the interactions of $Default$ and $FitchMktSh$ will be positive, consistent with greater rating optimism prior to default when competition from Fitch is higher. Second, we estimate an augmented version of equation (3) which adds $FitchMktSh$ and an interaction between $Optimism$ and $FitchMktSh$. If reputational risk concerns are important determinants of our primary findings, we expect the coefficient on the interaction of $Optimism$ and $FitchMktSh$ will be negative, suggesting that rating optimism has less predictive ability for recovery rates when competition from Fitch is higher.

Panel A of Table 6 reports the effect of industry competition from Fitch on rating adjustments prior to default. We re-center $FitchMktSh$ at its sample mean value to ease interpretation of the $Default$ coefficients. The coefficients on $Default$ are significantly negative. In addition, the coefficient estimates grow increasingly negative leading up to default. F-tests of the differences between the coefficients on $Default_{t-3mo}$ and $Default_{t-12mo}$ and the coefficients on $Default_{t-3mo}$ and $Default_{t-24mo}$ reject the null hypothesis of no difference at the 0.01 level (two-sided). Also, the coefficients on the interactions between $Default$ and $FitchMktSh$ are significantly positive. This evidence indicates that rating adjustments are relatively more optimistic when there is greater rating competition from Fitch.

Panel B of Table 6 reports the effect of Fitch competition on the predictive ability of rating adjustments for default recovery rates. For convenience, we re-center $Optimism$ at its sample mean value. Consistent with the evidence provided in Table 5, the coefficients on $PredictedRating$ and $Optimism$ are both positive and statistically significant at the 0.01 level. These findings suggest that more favorable expected credit ratings and greater rating adjustments, respectively, are positively associated with greater creditor recovery rates upon default. The estimated coefficient on the interaction $Optimism \times FitchMktSh$ is negative and statistically significant at the 0.01 level ($t = -3.90$). Thus, the same level of optimism in rating adjustments is less predictive of future default recoveries for firms in industries with a more competitive ratings environment. Specifically, for a firm in an industry at the median level of Fitch market share, the coefficient is nearly 86 percent smaller than for a firm in an industry with no presence from Fitch. Overall, it appears that reputational concerns have an economically significant impact on how optimistic rating adjustments are prior to default, as well as how informative rating agencies' adjustments are regarding recoveries given default. Thus, our primary findings do not appear to be solely driven by greater information sharing by default firms pre-default.

4.4 Sensitivity to borrower accounting conservatism

Recent evidence by Donovan et al. (2015) demonstrates that recovery rates are higher for firms with more conservative accounting practices. This evidence suggests that such practices lead to earlier covenant violations when negative shocks to borrowers' creditworthiness occur. In our investigation, more conservative accounting practices should be captured in predicted credit ratings through reported profitability. More conservative accounting practices, however, could limit the rating agencies' ability to use optimistic rating adjustments prior to default. We control for this possibility by including a conservatism variable in our default recovery analyses. Following Beatty et al. (2008) and Donovan et al. (2015), we measure *Conservatism* as the difference between the skewness of both operating cash flows and earnings for the three years prior to default. Greater accounting conservatism is expected to lead to earnings being more negatively skewed relative to operating cash flows. Accordingly, higher values of *Conservatism* correspond to more conservative accounting practices. The skewness measure is chosen over alternative measures because it provides us with the largest sample size, coupled with the fact that it does not rely on stock returns, which incorporate information in disclosed credit ratings.

In Table 7 we re-estimate our results from Table 5 and Panel B of Table 6 when *Rating* is measured at year $t-1$ after controlling for *Conservatism*. Similar to Donovan et al. (2015) when they use skewness to measure conservatism, we find that while accounting conservatism is positively associated with default recoveries in both columns (1) and (2) the coefficient is not statistically significant at conventional significance levels. In addition, we continue to find that the coefficients on $PredictedRating$ and $Optimism$ are both positive and statistically significant at the 0.01 level (two-sided) in columns (1) and (2). Finally, we find that the estimated coefficient on the interaction $Optimism \times FitchMktSh$ is negative and statistically significant at the 0.01 level (two-sided) in column (2). Overall, our earlier inferences are not altered after taking into account the influence of accounting conservatism on default recoveries.

5 Conclusion

Credit rating agencies have faced scrutiny following perceived rating failures in the early 2000s (e.g., Enron, 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 credit rating adjustments for firms that eventually default. 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 soft adjustments can allow credit rating agencies to become more conservative in their credit rating assessments as default approaches. Therefore, we first examine whether firms that eventually default exhibit reduced (increased) optimism (pessimism) as the default date approaches. We then examine whether optimism is positively associated with recovery rates upon default. We find results consistent with both predictions.

The possibility exists that issuers increasingly share private information with rating agencies if they believe default is imminent. For instance, firms typically have restructuring plans in place pre-default, which they may disclose in an effort to avoid "surprise" default events. However, prior research suggests that heightened rating agency competition reduces incumbent rating agencies' reputational risk, resulting in lower quality ratings when competition in a given industry increases. If our primary findings are driven by heightened reputational risk, rather than greater information sharing, we expect greater rating agency competition to weaken our findings of reduced optimism prior to default, as well as the association between rating adjustments and creditor recovery rates. Therefore, we examine whether greater Fitch market share in a given industry affects Moody's rating adjustments and ability to adequately assess creditor recovery risk. We find results consistent with these predictions. Accordingly, while our primary results suggest that reputational risk disciplines credit rating agencies when assessing default firms' credit risk, our results also indicate that reputational risk is downplayed by incumbent rating agencies when the threat of lost market share, and thus lower future economic rents from issuers, increases.

Our study offers several contributions. First, while findings in prior research suggest that rating adjustments are used opportunistically, our findings imply that incentives under the issuer-pay compensation model are diminished when reputational concerns amongst rating agencies are arguably the greatest—i.e., when firms approach default. Accordingly, our study sheds light on when rating agencies use their adjustments defensively. Second, while our results extend prior research by documenting that heightened competition impacts rating agencies' monitoring functions even in instances when external monitoring by market participants is potentially high, they also suggest that rating agencies allow their reputations to wane even in instances when failing to provide accurate credit risk assessments may hurt them the most. Third, we extend prior literature which examines the determinants of creditor recovery rates by providing evidence that subjective adjustments to model-based ratings are informative about recovery rates in default. In addition, while prior research provides mixed evidence as to the impact of increased rating stringency on creditor recovery rates over time, our findings offer further evidence that increased stringency has a reduced impact on creditor recovery rates when rating agency competition increases. Given this, market participants should use caution when using ratings as a barometer for default recoveries in their analysis.

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Appendix – Variable definitions

$DefaultPrice$ = 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 Default and Recovery Database [DRD]).

$Default$ = Indicator variable equal to one if observation pertains to a default firm, and zero otherwise.

$Optimism$ = $Rating - \hat{Rating}$. The $Optimism$ variable takes on positive values when actual ratings are higher than predicted ratings, and negative values when actual ratings are lower than predicted ratings.

$PredictedRating$ = 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. These factors lead to the following ordered probit model (estimated annually):

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

$Rating$ = Moody's historical issuer rating mapped to natural numbers such that higher numbers indicate higher rating quality, i.e., C = 1, ..., Aaa = 21 (www.moodys.com).

$IntCov$ = Earnings before interest, taxes, depreciation, and amortization divided by interest expense (EBITDA / XINT, Compustat).

$Profit$ = Earnings before interest, taxes, depreciation, and amortization divided by sales (EBITDA / REVT, Compustat).

$Book\_Lev$ = The sum of long- and short-term debt divided by total assets ((DLTT + DLC) / AT, Compustat).

$Size$ = Natural logarithm of total assets (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).

$Neg.Debt/EBITDA$ = Indicator variable equal to one if $Debt/EBITDA < 0$, and zero otherwise.

Vol = Standard deviation of $Profit$ over the prior five fiscal years; a minimum of two years required.

$Cash/Assets$ = Cash and short-term investments divided by total assets (CHE / AT, Compustat).

$ConvDe/Assets$ = Convertible debt divided by total assets (DCVT / AT, Compustat).

$Rent/Assets$ = Rent expense divided by total assets (XRENT / AT, Compustat).

$PPE/Assets$ = Net property, plant, and equipment divided by total assets (PPENT / AT, Compustat).

$CAPEX/Assets$ = Capital expenditures divided by total assets (CAPX / AT, Compustat).

$Coupon$ = The initial annual payment for a bond expressed as a percentage of the face amount (*COUP_RATE*, 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 Default and Recovery Database [DRD]).

$Subordinated$ = An indicator variable equal to one if the debt instrument is subordinated, and zero otherwise (*DEBT_SENR_CD*, DRD, Moody's Default and Recovery Database [DRD]).

$DistressedExchange$ = An indicator variable equal to one if the default type is distressed exchange, and zero otherwise (*DEF_TYP_CD*, DRD, Moody's Default and Recovery Database [DRD]).

$Chapter11$ = An indicator variable equal to one if the default type is Chapter 11 bankruptcy, and zero otherwise (*DEF_TYP_CD*, DRD, Moody's Default and Recovery Database [DRD]).

$Equity$ = Market value of equity, measured as common shares outstanding times closing stock price, divided by total assets (*(CSHO * PRCC_F)* / AT, Compustat).

$DefaultBarrier$ = 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).

$LTDIssuance$ = The ratio of long-term debt to total debt (*DLTT / [DLC + DLTT]*, 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).

$Intangibility$ = Intangible assets divided by total assets (*INTAN* / *AT*, Compustat)

$Receivables$ = Total receivables divided by total assets (*RECT* / *AT*, Compustat)

$Log(TotalAssets)$ = The natural logarithm of total assets (*AT*, Compustat).

$Log(Employees)$ = The natural logarithm of the number of employees (*EMP*, Compustat).

$FitchMktSh$ = The proportion of new bond ratings issued by Fitch in year t for firm *i's* two-digit NAICS industry (Mergent FISD).

$Conservatism$ = The difference between the skewness of both operating cash flows and earnings for the three years prior to default (Compustat).

Table 1: Descriptive Statistics

Panel A: Rating model sample

	Mean	Std. Dev.	Q1	Median	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
Size	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: Default sample

	Mean	Std. Dev.	Q1	Median	Q3
DefaultPrice	41.040	27.027	21.250	34.750	61.880
Optimism	-2.510	3.688	-4.000	-3.000	0.000
PredictedRating	8.472	4.478	5.000	8.000	1
Coupon	8.879	2.800	7.400	9.062	10.750
SeniorSecured	0.073	0.260	0.000	0.000	0.000
Subordinated	0.066	0.248	0.000	0.000	0.000
DistressedExchange	0.210	0.407	0.000	0.000	0.000
*Chapter*11	0.493	0.500	0.000	0.000	1
Equity	0.189	0.220	0.059	0.104	0.273
DefaultBarrier	0.351	0.261	0.237	0.299	0.386
LTDIssuance	0.822	0.233	0.748	0.895	0.982
Profitability	0.044	0.114	-0.011	0.068	0.113
Intangibility	0.108	0.178	0.000	0.009	0.162
Receivables	0.089	0.088	0.032	0.065	0.126
Log(*TotalAssets*)	8.080	1.621	7.246	7.796	9.107
Log(*Employees*)	2.196	1.732	1.035	2.563	3.025

Table 1 presents descriptive statistics for the variables used in our analyses. Panel A presents statistics for the variables used in the predicted credit rating model, while Panel B presents statistics for the variables used to test our hypotheses. All firm specific variables have been winsorized at the 1st and 99th percentiles. See the Appendix for variable definitions.

Table 2: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DefaultPrice$ (1)		0.071*	0.060*	-0.033	0.220***	-0.056	0.332***	-0.265***
$Optimism$ (2)	0.098***		-0.768***	0.147***	-0.028	0.115***	0.085**	-0.360***
$PredictedRating$ (3)	0.105***	-0.711***		-0.272***	-0.005	-0.049	-0.091**	0.195***
$Coupon$ (4)	-0.013	0.131***	-0.189***		0.070*	-0.094**	-0.242***	0.030
$SeniorSecured$ (5)	0.234***	-0.023	-0.034	0.085**		-0.074*	-0.086**	0.127***
$Subordinated$ (6)	-0.052	0.123***	-0.058	-0.083**	-0.074*		0.031	-0.125***
$DistressedExchange$ (7)	0.332***	0.057	-0.083**	-0.234***	-0.086**	0.031		-0.508***
$Chapter11$ (8)	-0.263***	-0.328***	0.174***	0.041	0.127***	-0.125***	-0.508***	
$Equity$ (9)	0.026	0.031	0.243***	-0.064*	-0.085**	0.063*	-0.063*	0.064*
$DefaultBarrier$ (10)	-0.096**	0.184***	-0.367***	-0.012	0.024	0.009	0.050	-0.118***
$LTDIssuance$ (11)	0.026	0.053	0.050	-0.036	-0.017	-0.050	0.185***	0.006
$Profitability$ (12)	-0.071*	-0.282***	0.264***	0.107***	-0.061*	0.002	-0.298***	0.163***
$Intangibility$ (13)	0.020	0.027	-0.056	-0.088**	-0.028	-0.054	0.115***	-0.182***
$Receivables$ (14)	-0.018	-0.091**	0.101***	-0.041	-0.026	0.108***	0.016	-0.149***
$Log(TotalAssets)$ (15)	0.005	-0.694***	0.744***	-0.322***	-0.064*	-0.136***	0.125***	0.215***
$Log(Employees)$ (16)	-0.087**	-0.519***	0.546***	-0.137***	-0.150***	-0.080**	-0.124***	0.280***

Correlations (continued)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$DefaultPrice$ (1)	0.185***	-0.123***	0.023	-0.041	-0.082**	-0.073*	0.025	-0.067*
$Optimism$ (2)	0.047	0.204***	0.091**	-0.290***	0.055	-0.007	-0.625***	-0.509***
$PredictedRating$ (3)	0.114***	-0.420***	-0.086**	0.243***	-0.069*	0.084**	0.730***	0.573***
$Coupon$ (4)	-0.024	0.025	-0.042	0.179***	-0.035	0.001	-0.406***	-0.163***
$SeniorSecured$ (5)	-0.078**	0.050	-0.021	-0.110***	-0.041	0.005	-0.041	-0.125***
$Subordinated$ (6)	0.088**	0.044	-0.029	-0.040	-0.021	0.099***	-0.143***	-0.072*
$DistressedExchange$ (7)	-0.037	0.201***	0.245***	-0.194***	0.109***	-0.136***	0.141***	-0.138***
$Chapter11$ (8)	0.088**	-0.206***	-0.062*	0.140***	-0.208***	-0.132***	0.226***	0.260***
$Equity$ (9)		-0.453***	0.142***	0.185***	-0.303***	-0.086**	0.022	0.001
$DefaultBarrier$ (10)	-0.228***		0.024	0.003	0.162***	-0.005	-0.267***	-0.353***
$LTDIssuance$ (11)	0.189***	-0.408***		0.109***	0.112***	-0.357***	-0.043	-0.222***
$Profitability$ (12)	0.066*	0.153***	-0.034		0.003	0.082**	-0.071*	0.159***
$Intangibility$ (13)	-0.141***	0.170***	0.053	0.178***		0.180***	-0.027	0.053
$Receivables$ (14)	0.008	0.098***	-0.290***	0.106***	-0.045		-0.121***	0.075*
$Log(TotalAssets)$ (15)	0.096**	-0.229***	0.049	-0.009	-0.028	0.022		0.651***
$Log(Employees)$ (16)	-0.003	-0.211***	-0.071*	0.205***	-0.055	0.109***	0.690***	

Table 2 presents Pearson and Spearman correlation for the variables used in our analyses. We report Pearson (Spearman) correlations above (below) the diagonal. 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. See the Appendix for variable definitions.

Table 3: Rating model estimation

	(1) *Rating*
$IntCov$	0.0061***
	(4.05)
$Profit$	0.0136
	(0.51)
$Book\_Lev$	-3.0014***
	(-17.53)
$Size$	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 3 presents a 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. Industry fixed effects are included based on Fama and French (1997) industry 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. See the Appendix for variable definitions.

Table 4: Average rating optimism prior to events of default

Panel A: Default-only sample

$Default_{t-3mo}$	-1.669
	(-10.15)
$Default_{t-6mo}$	-1.331
	(-8.14)
$Default_{t-9mo}$	-1.086
	(-6.71)
$Default_{t-12mo}$	-1.022
	(-6.29)
$Default_{t-15mo}$	-1.002
	(-5.98)
$Default_{t-18mo}$	-0.934
	(-5.39)
$Default_{t-21mo}$	-0.828
	(-4.93)
$Default_{t-24mo}$	-0.826
	(-4.92)
F-test: $Default_{t-3} = Default_{t-12}$	39.99***
F-test: $Default_{t-3} = Default_{t-24}$	44.56***

Table 4 – continued

Panel B: Matched sample

	(1) Default	(2) Non-Default	(3) Diff.
$Default_{t-3mo}$	-1.669	-0.102	-1.566***
	(-10.15)	(-0.58)	(-6.60)
$Default_{t-6mo}$	-1.331	-0.145	-1.186***
	(-8.14)	(-0.81)	(-4.99)
$Default_{t-9mo}$	-1.086	-0.124	-0.962***
	(-6.71)	(-0.71)	(-4.10)
$Default_{t-12mo}$	-1.022	-0.067	-0.955***
	(-6.29)	(-0.41)	(-4.20)
$Default_{t-15mo}$	-1.002	-0.110	-0.893***
	(-5.98)	(-0.67)	(-3.87)
$Default_{t-18mo}$	-0.934	-0.140	-0.793***
	(-5.39)	(-0.88)	(-3.40)
$Default_{t-21mo}$	-0.828	-0.136	-0.692***
	(-4.93)	(-0.87)	(-3.05)
$Default_{t-24mo}$	-0.826	-0.160	-0.666***
	(-4.92)	(-1.00)	(-2.90)
F-test: $Default_{t-3} = Default_{t-12}$	39.99***	0.17	20.79***
F-test: $Default_{t-3} = Default_{t-24}$	44.56***	0.27	29.11***

Table 4 presents the average rating optimism at three-month intervals over the two-year period prior to default. Panel A presents only the actual default observations while Panel B presents both default observations and industry-year matched non-default observations. 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. See the Appendix for variable definitions.

Table 5: Default recoveries and pre-default credit ratings

	$DefaultPrice$	
	(1)	(2)
	Rating at Year $t-1$	Rating at Year $t-2$
$PredictedRating$	2.664^{***}	2.764^{***}
	(3.57)	(3.61)
$Optimism$	2.058^{***}	1.747^{***}
	(3.51)	(3.15)
$Coupon$	0.352	0.467
	(1.08)	(1.34)
$SeniorSecured$	22.923^{***}	19.856^{***}
	(5.45)	(4.21)
$Subordinated$	-2.687	-0.022
	(-0.61)	(-0.00)
$DistressedExchange$	28.907^{***}	28.564^{***}
	(8.07)	(8.05)
$Chapter11$	-5.823^{**}	-8.055^{**}
	(-2.08)	(-2.45)
$Equity$	-2.467	-6.585^{**}
	(-0.37)	(-2.04)
$DefaultBarrier$	-10.857^{**}	-9.622
	(-2.08)	(-0.91)
$LTDIssuance$	-17.355^{***}	-10.667
	(-3.26)	(-1.10)
$Profitability$	-8.620	6.855
	(-0.57)	(0.84)
$Intangibility$	-3.624	-5.843
	(-0.47)	(-0.72)
$Receivables$	-2.587	-7.483
	(-0.22)	(-0.47)
$Log(TotalAssets)$	-5.313^{**}	-5.208^{**}
	(-2.53)	(-2.34)
$Log(Employees)$	1.860	1.508
	(1.32)	(0.94)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Observations	1,126	1,091
Adjusted R^2	0.537	0.515
F-test: $PredictedRating = Optimism$	0.80	2.00

Table 5 presents the results from estimation of a regression of default recoveries and pre-default credit ratings. 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. See the Appendix for variable definitions.

Table 6: The effect of competition from Fitch

Panel A: Rating adjustments sample

	(1) $RatingOptimism$
$Default_{t-3mo}$	-1.612***
	(-5.88)
$Default_{t-6mo}$	-1.281***
	(-4.72)
$Default_{t-9mo}$	-0.875***
	(-3.40)
$Default_{t-12mo}$	-0.839***
	(-3.17)
$Default_{t-15mo}$	-0.878***
	(-3.44)
$Default_{t-18mo}$	-0.741***
	(-2.77)
$Default_{t-21mo}$	-0.530**
	(-2.04)
$Default_{t-24mo}$	-0.504**
	(-1.99)
$FitchMktSh \times Default_{t-3mo}$	3.039***
	(6.22)
$FitchMktSh \times Default_{t-6mo}$	2.259***
	(3.16)
$FitchMktSh \times Default_{t-9mo}$	2.030***
	(3.81)
$FitchMktSh \times Default_{t-12mo}$	2.111***
	(3.12)
$FitchMktSh \times Default_{t-15mo}$	1.945***
	(3.45)
$FitchMktSh \times Default_{t-18mo}$	1.861***
	(3.84)
$FitchMktSh \times Default_{t-21mo}$	1.646***
	(3.34)
$FitchMktSh \times Default_{t-24mo}$	2.916***
	(5.85)
Observations	3,624
Adjusted R^2	0.118
F-test: $Default_{t-3} = Default_{t-12}$	15.34***
F-test: $Default_{t-3} = Default_{t-24}$	20.35***

Table 6 – continued

Panel B: Default recoveries sample

	(1)
	$DefaultPrice$
$PredictedRating$	2.865***
	(4.34)
$Optimism$	2.765***
	(4.06)
$FitchMktSh$	11.427
	(0.54)
$Optimism \times FitchMktSh$	-17.609***
	(-3.90)
$Coupon$	0.354
	(1.09)
$SeniorSecured$	22.750***
	(5.56)
$Subordinated$	-4.052
	(-0.94)
$DistressedExchange$	29.832***
	(7.91)
$Chapter11$	-5.651
	(-1.95)
$Equity$	0.122
	(0.02)
$DefaultBarrier$	-8.937
	(-1.79)
$LTDIssuance$	-15.884***
	(-3.07)
$Profitability$	-14.781
	(-1.01)
$Intangibility$	-1.775
	(-0.22)
$Receivables$	-0.302
	(-0.03)
$Log(TotalAssets)$	-6.433***
	(-3.05)
$Log(Employees)$	2.041
	(1.45)
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
Observations	1,126
Adjusted R^2	0.542

Table 6 presents the results from examining the effects of competition from Fitch on credit rating adjustments prior to default and default recoveries. Panel A presents results for the rating adjustments sample while Panel B presents results for the default recoveries sample. 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. See the Appendix for variable definitions.

Table 7: Sensitivity test: Default recoveries and pre-default credit ratings controlling for accounting conservatism

	(1) $DefaultPrice$	(2) $DefaultPrice$
$PredictedRating$	2.671***	2.846***
	(3.59)	(4.36)
$Optimism$	2.059***	2.699***
	(3.47)	(3.97)
$FitchMktSh$		12.113
		(0.56)
$Optimism \times FitchMktSh$		-18.622***
		(-4.11)
$Conservatism$	2.131	1.981
	(1.39)	(1.28)
$Coupon$	0.353	0.356
	(1.08)	(1.09)
$SeniorSecured$	22.937***	22.768***
	(5.49)	(5.60)
$Subordinated$	-3.437	-4.655
	(-0.79)	(-1.08)
$DistressedExchange$	28.986***	29.815***
	(8.20)	(8.01)
$Chapter11$	-6.126**	-5.969**
	(-2.22)	(-2.10)
$Equity$	-1.399	1.014
	(-0.21)	(0.16)
$DefaultBarrier$	-10.327**	-8.616*
	(-2.04)	(-1.80)
$LTDIssuance$	-17.237***	-15.906***
	(-3.22)	(-3.06)
$Profitability$	-8.895	-14.403
	(-0.59)	(-0.99)
$Intangibility$	-3.621	-1.815
	(-0.47)	(-0.23)
$Receivables$	-0.906	1.272
	(-0.08)	(0.11)
$Log(TotalAssets)$	-5.110**	-6.171***
	(-2.41)	(-2.89)
$Log(Employees)$	1.833	2.014
	(1.31)	(1.44)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Observations	1,125	1,125
Adjusted R^2	0.539	0.543

Table 7 presents the results from estimating the association between default recoveries and pre-default credit ratings controlling for accounting conservatism. 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. See the Appendix for variable definitions.