Are Credit Ratings More Rigorous for Widely Covered Firms?

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ABSTRACT: We study how business press coverage can discipline credit rating agency actions. Because of their greater prominence and visibility to market participants, more widely covered firms can pose greater reputational costs for rating agencies. Consistent with rating agencies limiting such risk, we find that ratings for more widely covered firms are more timely and accurate, downgraded earlier and systematically lower in the year prior to default, and better predictors of default and non-default. We also find that the recent tightening of credit rating standards is largely explained by growing business press coverage of public debt issuers. Additionally, we find that credit rating agencies take explicit actions to improve their ratings by assigning better educated and more experienced analysts to widely covered firms. Moreover, we document that missed defaults of more visible firms create greater negative economic consequences for rating agencies, and that rating improvements following the financial crisis were greater for more visible firms.

Data Availability: All data are publicly available from the sources identified in the text.

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I. INTRODUCTION

The timeliness and accuracy of credit ratings have been the subject of considerable attention from investors, regulators, politicians, academic researchers, and journalists. During the early 2000s, the failure of the major credit rating agencies to provide timely information prior to large defaults (e.g., Enron and WorldCom) attracted significant scrutiny.[1] In the late 2000s, the failure of the rating agencies to issue accurate ratings of subprime mortgages and to timely downgrade Lehman Brothers' commercial paper before the financial crisis brought further scrutiny. Following these failures, both the U.S. Congress and the Securities and Exchange Commission (SEC) reviewed the performance and standards of credit rating agencies. These reviews incited further criticism and skepticism regarding whether credit rating agencies needed greater regulatory oversight. For instance, a 2002 Senate committee report following the rating failures at Enron and other large bankrupt corporations concludes that "it is difficult not to wonder whether lack of accountability—the agencies' practical immunity to lawsuits and non-existent regulatory oversight—is a major problem" (U.S. Senate Committee on Governmental Affairs 2002, 116). These

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[1] For instance, the major credit rating agencies' failure to downgrade Enron in 2001 to below investment grade until four days prior to its bankruptcy filing caused considerable public criticism and regulatory scrutiny.

concerns highlight the importance of understanding the mechanisms that lead to more or less rigorous ratings and raise concerns that the credit rating agencies cannot self-govern when regulatory scrutiny is limited.

This study investigates whether credit rating agencies are more rigorous for issuers with greater business press coverage. Although not directly intended by the business press, the greater prominence and visibility of widely covered issuers can create reputational risk for the credit rating agencies (e.g., Mathis, McAndrews, and Rochet 2009; Bolton, Freixas, and Shapiro 2012; Bar-Isaac and Shapiro 2013). This occurs for at least two primary reasons. First, greater business press coverage leads to greater production and dissemination of information (e.g., Bushee, Core, Guay, and Hamm 2010; Soltes 2011; Drake, Guest, and Twedt 2014; Peress 2014; Twedt 2016; Bushman, Williams, and Wittenberg-Moerman 2017; Blankespoor, deHaan, and Zhu 2018), which can increase investors' and creditors' awareness regarding issuers' financial performance and default risk. Accordingly, greater business press coverage can lead to a richer information environment and an increased ability of bond market participants to detect untimely or inaccurate ratings. The ability of the business press to draw attention and affect trading decisions not only extends to individual investors (Barber and Odean 2008), but also to professional investors (Fang, Peress, and Zheng 2014). The role of disseminating news is considerable. During our sample period of 2001 to 2011, there were over ten million news stories on the Dow Jones Edition of RavenPack, which includes stories from Dow Jones Newswires, *Barron's,* the *Wall Street Journal* (*WSJ*), and other Dow Jones news products. Regarding the reach of the business press, the *Wall Street Journal* alone has a print circulation of over two million subscribers (Alliance for Audited Media [AAM) 2013]. When considering the electronic dissemination of news stories, the circulation of company news is even broader: The *Wall Street Journal* has over 21 million digital readers (*WSJ* 2014). Further, the reach of the business press has grown considerably over our sample period. As shown in Figure 1, the number of annual news stories for firms with public credit ratings increased from a median of 145 stories in 2001 to over 400 stories by 2011.[2] Second, because of greater reader interest, the business press is more likely to serve as a "watchdog" for widely covered firms by providing original investigative reports and uncovering accounting frauds (Miller 2006). Relative to the dissemination role, the watchdog role performed by the business press is much less prevalent; however, watchdog-related coverage can draw considerable attention from market participants and regulators.[3] For the credit rating agencies, the discovery and broadcast of untimely or inflated ratings can impair their reputation as high-quality certification intermediaries and reduce their future economic rents arising from reduced demand for their ratings (Bonsall 2014). We, therefore, expect that greater business press coverage of issuers leads the rating agencies to issue and maintain more accurate and timely ratings.

Our empirical tests provide support for business press coverage disciplining the major rating agencies. In rating timeliness tests, we find that defaulting issuers with greater coverage are downgraded earlier relative to the default date and have lower average ratings in the year before default. These differences in timeliness are economically large. An interquartile range increase in coverage leads to ratings that are downgraded over a month earlier prior to default, and average ratings in the year before default that are lower by approximately 0.91 notches (i.e., almost a full letter rating reduction). These findings of greater timeliness for defaulting issuers are of particular interest, as the properties of ratings before default are the most commonly scrutinized aspect of credit rating quality (e.g., SEC 2003).

In rating accuracy tests, we find that rating agencies provide ratings for issuers with greater business press coverage with less frequent Type I (i.e., missed defaults) and Type II (i.e., false warnings) errors.[4] The error rates for widely covered issuers are significantly lower. An interquartile range increase in business press coverage leads to a 12 percent lower rate in Type I errors and an 86 percent lower rate in Type II errors. Also, in tests examining rating stringency (i.e., more conservative ratings), we find that business press coverage, which has increased considerably over time, is an important mediating variable for the growth in rating stringency observed since 2001.[5] Using year indicator variables in a credit rating determinants model, similar to Alp (2013) and Baghai, Servaes, and Tamayo (2014), we confirm that average ratings have become systematically lower from 2001 to 2011—falling by approximately 1.2 notches. When we include business press coverage as a mediating variable, we find that the mediated path through business press coverage explains a large portion of the increase in rating stringency. In additional analyses, similar to Alp (2013) and Baghai et al. (2014), we find that the increased rating stringency occurs for both

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[2] The possibility exists that the dramatic growth in aggregate coverage could reduce the salience or visibility of individual news stories to market participants.

[3] In recent years, the dissemination role of the business press has become increasingly relevant (e.g., Blankespoor et al. 2018), with the investigative role becoming stagnant or falling. This suggests that the business press has faced a shift in demand to produce more low-cost stories relative to original content.

[4] While seemingly not as directly tied to reputational risk incentives as missed defaults, our findings of lower false warnings of default are in line with credit rating agencies applying more rigorous standards for issuers with greater business press coverage.

[5] Alp (2013) shows that there was a shift in the stringency of rating standards from 2002 to 2007, with ratings falling, on average, by 1.5 notches. Baghai et al. (2014) show that rating stringency increased from 1985 to 2009, on average, by three notches and, similar to Alp (2013), that stringency increased dramatically from 2002 to 2009. Alp (2013) and Baghai et al. (2014) find that the conservative bias in ratings is reflected in bond yield spreads, consistent with more stringent ratings being more accurate.
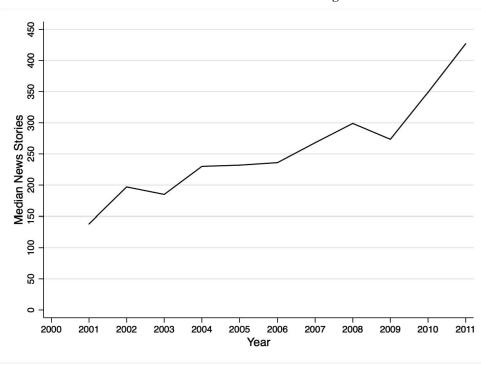
FIGURE 1
Growth in Business Press Coverage

This figure presents the median number of new stories per year written about public debt issuers in our sample over the 2001–2011 period. The number of news stories is obtained from RavenPack.

investment- and speculative-grade issuers, but is more pronounced for investment-grade issuers. For both subsamples, we further find that the mediated path through business press coverage is responsible for a significant amount of the increase in rating stringency.

To examine the economic mechanism through which the credit rating agencies improve rating quality, in additional tests, we investigate whether rating agencies strategically assign their "better" analysts to widely covered issuers. As shown in Fracassi, Petry, and Tate (2016), credit rating analysts with better education or more experience can have greater ability to synthesize information to produce higher quality ratings. For widely covered firms, we find that the credit rating agencies more frequently assign analysts with an M.B.A. and with an M.B.A. from a top five school, that are female and older, with greater tenure in the industry and the agency, and with greater issuer coverage. We fail to find similar evidence for analysts with greater tenure with the issuer, possibly reflecting agency problems through extended relationships between managers and individual analysts. These findings indicate that heightened monitoring occurs for widely covered issuers through the use of higher quality analysts.

Importantly, business press coverage can capture factors other than the visibility of issuers (see Engelberg and Parsons [2011] for greater discussion). To limit the possibility that some other aspect of business press coverage is responsible for our findings, following Fang and Peress (2009), Bushee et al. (2010), and Hillert, Jacobs, and Müller (2014), we use an extensive set of control variables to account for cross-sectional differences in business press coverage and other issuer characteristics. Combined, these variables explain a large portion of the variation in business press coverage. To limit potential reverse causality, we measure business press coverage prior to the period when the properties of credit ratings are examined. This construction minimizes the possibility that business press coverage is caused by events that lead to ratings changes (e.g., loss of a major customer). We also limit the influence of omitted variables on our inferences through an instrumental variables model using two-stage least squares and find that our inferences are unchanged using this alternative approach. In addition, we investigate whether the sentiment of news stories is responsible for our findings, as the business press tends to cover more negative news (Gurun and Butler 2012). Negative bias in coverage could lead to an association between coverage and the properties of credit ratings in some of our analyses—e.g., more widely covered issuers could be those with more prior negative news and, accordingly, lower ratings. While we control for the information released to the market using stock returns, we also

allow for differences in the sentiment of news stories. We find that the number of positive sentiment stories is an important determinant of ratings quality, but fail to find that the number of negative sentiment stories is relatively more important. Further, the prominence and quality of the media outlet could have a more pronounced effect on how business press coverage affects the properties of ratings. Consistent with this prediction, we find that *WSJ* coverage, an outlet with large and public coverage and known for high-quality reporting, has an incremental impact on rating timeliness, accuracy, and stringency.

Despite these steps, the richer information environment brought about by greater business press coverage could still confound our inferences. Specifically, despite the major credit rating agencies having access to material nonpublic information, formerly through their exemption from Regulation Fair Disclosure and currently through the use of nondisclosure agreements, more widely covered firms could have more timely and accurate ratings because of more information being increasingly available (e.g., Bushee et al. 2010; Soltes 2011; Drake et al. 2014; Peress 2014; Twedt 2016; Bushman et al. 2017). In addition, due to the increased threat of legal action against firms for not disclosing bad news (Skinner 1997; Kothari, Shu, and Wysocki 2009), a richer information environment could make it particularly difficult for issuers' management to not disclose negative information and, accordingly, for credit rating agencies to not incorporate such news into ratings. To bolster our reputational harm interpretation of the findings, we conduct additional tests that focus on the reputational consequences for missed default predictions. Consistent with greater reputational harm, we find that missed defaults for more widely covered firms lead to greater business press discussion of the rating agency, reduced demand for coverage of new issuances in the same industry, less responsive stock returns to later ratings changes made by the rating agency in the same industry, and greater economic losses for rating agencies (i.e., negative default announcement stock returns for Moody's). We also find that missed defaults lead the rating agencies to improve the quality of ratings for other firms with greater visibility in the same industry, and for other firms in the same industry when the defaulting firm was more visible. Other analysis shows that the rating agencies accomplish these changes, in part, through the assignment of higher quality analysts to new issuances.

Further, the existence of rating failures for high-visibility issuers during periods of limited regulatory scrutiny (e.g., WorldCom in the early 2000s and Lehman Brothers in the late 2000s) raises the possibility that the rating agencies exercise less care during such times. Such behavior is consistent with the theory of the cyclicality of reputation building put forth by Mathis et al. (2009) and the empirical findings of Dimitrov, Palia, and Tang (2015) and deHaan (2017). They show that corporate ratings quality improved following the regulatory scrutiny and oversight brought about by rating failures for structured finance products during the financial crisis. In additional tests, we examine if stronger regulatory regimes lead to more rigorous ratings for widely covered issuers. Our findings support this possibility.

This study contributes to the literature that examines the role of reputation in the credit rating industry. Prior theoretical work on product quality has established the high returns to creating a positive reputation (Klein and Leffler 1981; Shapiro 1983). With respect to credit rating agencies, Mathis et al. (2009) model reputational incentives in a monopolist rating agency and find that reputation can discipline rating agencies when income from rating less complex products and the proportion of successful projects are sufficiently high. Otherwise, reputation building appears to yield what Mathis et al. (2009) refer to as "inefficient confidence cycles." Bolton et al. (2012) model competition in the credit rating market and find that rating inflation is a decreasing function of reputational costs. Bar-Isaac and Shapiro (2013) show that rating quality is countercyclical in a model of endogenous reputation, and that higher reputational losses lead to greater incentives for accurate ratings. Empirically, Cheng and Neamtiu (2009) document an improvement in the accuracy, timeliness, and stability of credit ratings from Standard & Poor's (S&P), Moody's, and Fitch following the high-profile corporate bankruptcies of the early 2000s. Dimitrov et al. (2015) and deHaan (2017) find that the credit rating agencies took actions (e.g., issued lower ratings) to protect their reputations following the financial crisis. Kraft (2015) shows that credit rating agencies cater to issuers using subjective rating adjustments when loan contracts have performance-pricing provisions, but that such catering is reduced when reputational costs are higher. Our study contributes to the rating agency reputation literature by showing that the business press provides a channel through which the major rating agencies face heightened reputational risk and that the rating agencies actively respond to this risk by assigning higher quality analysts.

In addition, this study relates to the extensive literature on the role of the business press in financial markets. Prior research has shown that the business press plays an important role in disseminating information to capital markets (e.g., Klibanoff, Lamont, and Wizman 1998; Miller 2006; Tetlock 2007; Tetlock, Saar-Tsechansky, and Macskassy 2008; Fang and Peress 2009; Bushee et al. 2010; Soltes 2011; Tetlock 2010; Engelberg and Parsons 2011; Griffin, Hirschey, and Kelly 2011; Solomon 2012; Ahern and Sosyura 2014; Drake et al. 2014; Fang et al. 2014; Hillert et al. 2014; Peress 2014; Solomon, Soltes, and Sosyura 2014; Twedt 2016; Bushman et al. 2017; Blankespoor et al. 2018) and providing new information through investigative reporting (Miller 2006). Other studies have highlighted the influence of the business press because business press coverage provides a focal point for market observers (Holthausen and Leftwich 1983; Erfle and McMillan 1990; Joskow, Rose, and Wolfram 1996; Pollock, Fischer, and Wade 2002; Core, Guay, and Larcker 2008). Further, this literature also provides some evidence that the business press can exert a governance role over company actions (Dyck, Volchkova, and Zingales 2008; Liu and McConnell 2013). Our paper adds to this literature by documenting that the business press can impose on credit rating

agencies reputational risk that leads to significant changes in the properties of credit ratings. This finding is important, as it demonstrates how prominence, in this case, visibility brought about by business press coverage, leads to a disciplining effect on an important monitor of firms.

This study also contributes to the literature on the tightening of standards by credit rating agencies. A significant amount of research has documented an increase in the stringency of corporate credit ratings over time. Blume, Lim, and Mackinlay (1998) show that during the period from 1978–1995, firms with the same financial ratios receive less favorable credit ratings, on average, in later years. Jorion, Shi, and Zhang (2009) document that only investment-grade firms appear to exhibit increasing stringency, and that the increasing stringency is explained by the changing rating relevance of accounting variables over time. Alp (2013) shows a structural shift in credit rating standards after 2002: increasing stringency at a faster pace for investment-grade firms and a reversal of looser rating standards for speculative grade firms. Finally, Baghai et al. (2014) show that ratings become more stringent from 1985–2009, and that the increased stringency is not fully warranted because defaults by rating categories fell during the sample period. While all of these studies have documented increasing rating stringency in at least some portion of the rating spectrum, other than Jorion et al. (2009), prior research has left unanswered the question of why corporate credit ratings have become more stringent over time. Our study provides an incentive-based explanation, namely, reputational risk imposed by increasing business press attention, for the empirical evidence of more stringent corporate credit rating standards.

The remainder of the paper proceeds as follows. Section II discusses prior theory and evidence related to reputational risk and credit rating agencies, and develops our research hypotheses. Section III discusses our sample. Sections IV and V provide our research design and empirical results for our primary analyses. Section VI provides additional analyses. Section VII summarizes and concludes.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

The Importance of Reputation to Credit Rating Agencies

Prior research demonstrates that the quality of ratings issued by the major credit rating agencies is determined by reputational costs. Bolton et al. (2012) show, for instance, that if investors learn that a credit rating agency issued inaccurate (e.g., inflated) ratings, then they will impose costs on the agency by lowering demand for future ratings. These reputational costs are higher as the risk of being caught by investors, issuers, or regulators grows. Further, as discussed by Mathis et al. (2009), the major credit rating agencies argue that being perceived as too sluggish can be extremely dangerous for them, drawing parallels to the auditing industry and the demise of Arthur Andersen following the scandal and bankruptcy of Enron.[6] While not as extreme, following their failure to downgrade Enron, WorldCom, and others until just days prior to sizable bankruptcies, the major credit rating agencies faced considerable harm to their reputations and extensive review by regulators (e.g., Securities and Exchange Commission 2003). In response to these failures, Congress passed the Credit Rating Agency Reform Act of 2006 on September 29, 2006 to increase regulatory oversight by the Securities and Exchange Commission (SEC) over Nationally Recognized Statistical Ratings Organizations (NRSROs). In addition, in response to the problems during the 2007–2008 financial crisis associated with the ratings of highly rated structured finance products and the failure to downgrade Lehman Brothers' commercial paper until the day of its bankruptcy, the major rating agencies faced public scrutiny, regulation through the Dodd-Frank Act of 2010 (Dodd-Frank), and civil lawsuits initiated by both the Justice Department and investors (Thomas, Hennessey, and Holtz-Eakin 2011; Freifeld 2013). For these reasons, credit rating agencies have incentives to provide timely and accurate ratings.

Recent empirical evidence suggests that the quality of ratings changed following highly visible threats to the reputation of the national credit rating agencies, consistent with the predictions of Mathis et al. (2009) and Bolton et al. (2012). Specifically, Cheng and Neamtiu (2009) find that the timeliness, accuracy, and stability of the NRSROs' ratings improved in the post-Enron period. Alp (2013) and Baghai et al. (2014) find a structural shift toward more stringent credit ratings in the post-Enron period. Dimitrov et al. (2015) show that credit ratings were lower, more likely to falsely predict default, and less informative for downgrades following the passage of Dodd-Frank. deHaan (2017) documents that rating performance improved and investors relied less on ratings following the damage to credit rating agencies' reputations brought about by the financial crisis.

These high visibility rating failures illustrate the importance of reputation to the credit rating agencies. However, similar to other businesses serving as quality certification intermediaries, the economic rents of the credit rating agencies are tied to their

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[6] Consistent with this argument, Standard & Poor's argued in a 2002 SEC hearing following Enron and other corporate failures: "Most importantly, the ongoing value of Standard & Poor's credit ratings business is wholly dependent on continued market confidence in the credibility and reliability of its credit ratings. No single issuer fee or group of fees is important enough to risk jeopardizing the agency's reputation and its future" (Securities and Exchange Commission 2003, 3).

reputation to provide timely and unbiased assessments (see Chemmanur and Fulghieri [1994] for a demonstration of incentives for banks to build and maintain reputations). Investor and issuer opinions that a credit rating agency is failing to provide quality ratings will lead to reduced demand for its ratings and lower future rating revenues. Accordingly, credit rating agencies face incentives to protect their reputations by maintaining high-quality ratings in general, not just before high-visibility events (e.g., issuer default).

Business Press Coverage of Issuers and Credit Rating Agencies' Incentives

The major rating agencies suggest that reputational harm from rating failures varies in the visibility of issuers. For example, Neil Baron, Vice Chairman and General Counsel of Fitch, wrote a comment letter to the SEC stating that "an unjustifiably favorable rating on any issue is destructive to our most important asset—our reputation—and therefore to our business. Unjustifiably favorable ratings are even more visible, and therefore more destructive to reputation, when they are assigned to larger issues" (Securities and Exchange Commission 2003). Accordingly, greater business press coverage of an issuer can create reputational risk for the major credit rating agencies. This can occur because greater coverage leads to increased production and dissemination of information to investors and creditors and, in extreme cases, business press criticism of rating failures. As documented by prior research, the business press serves an important role in financial markets through its dissemination of information (e.g., Miller 2006; Bushee et al. 2010; Soltes 2011; Peress 2014; Drake et al. 2014; Twedt 2016; Bushman et al. 2017; Blankespoor et al. 2018) and investigative reporting (e.g., Dyck et al. 2008; Miller 2006). For the rating agencies, increased dissemination leads to greater and broader awareness by market participants of firms' fundamentals, as coverage draws and concentrates the attention of market observers. This can have the unintentional effect of greater business press coverage facilitating users' ability to detect untimely or biased credit ratings.[7] This can also occur because, in addition to regulators and investors, the business press frequently criticizes the major credit rating agencies for failing to incorporate information into ratings in a timely fashion, or failing to respond at all (for examples, see Voigt 2010; Pym 2012; Krantz 2013). Thus, broader business press coverage can significantly influence the perceptions of market participants and, in extreme instances, of regulators and the general public regarding apparent rating failures by the credit rating agencies.

Rating agencies can issue more timely ratings to mitigate the reputational risk arising from more widely covered issuers. Similar to other information intermediaries, credit rating agencies are expected to provide timely information to equity and debt market participants regarding changes in issuers' creditworthiness. The potential greater reputational harm for failing to provide updated ratings for more widely covered issuers is expected to result in more timely ratings for such issuers. We state this prediction more formally in our first research hypothesis (in alternative form):

H1: Credit ratings issued by the major credit rating agencies are more timely for issuers with greater business press coverage.

These reputational incentives also lead us to predict that the credit rating agencies will be more accurate with their ratings for issuers with greater business press coverage. The rating agencies can improve both their timeliness and accuracy by using better rating methods and credit analysts and by increasing effort. The major rating agencies, however, face important constraints on their actions because of the higher cost of improving their methods, using better analysts, and increasing their effort and because of their position as NRSROs. For instance, credit ratings of NRSROs provide an important contracting function: serving as inputs in debt contracts, being used for regulatory purposes (e.g., the eligibility of issuers to use a shortened prospectus), and serving as a governance mechanism for portfolio managers when setting or monitoring bond holdings. This creates costs for issuers and users when ratings are unduly optimistic or pessimistic. In line with the importance of such costs, NRSROs argue that they face incentives to gradually change their ratings only after receiving corroborating and detailed information regarding changes in issuers' credit quality (see Watts [2003] for further discussion). Accordingly, a natural trade-off can exist between the timeliness and accuracy of credit ratings. Specifically, if rating agencies incorporate the arrival of new information into credit ratings too quickly and shorten the time period used to gather and analyze information, then the accuracy of their ratings could decline. Because of these different possibilities in managing timeliness and accuracy, we do not make a directional prediction for our second hypothesis:

H2: Credit ratings issued by the major credit rating agencies differ in their accuracy for issuers with greater business press coverage.

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[7] In theory, litigation risk arising from Rule 10b-5 could also provide a deterrent for untimely or biased credit ratings. However, over time, both state and federal courts have granted credit rating agencies First Amendment protections, which take the agencies out of the purview of Rule 10b-5 (Schmitt 2011).

Does Increased Business Press Coverage Contribute to Growing Credit Rating Stringency?

Recent work by Alp (2013) and Baghai et al. (2014) provides evidence that credit rating standards have grown considerably more stringent over time, particularly since 2002.[8] Alp (2013) shows that there was a shift in the stringency of rating standards from 2002 to 2007, with ratings falling, on average, by 1.5 notches. Baghai et al. (2014) show that rating standards declined from 1985 to 2009, on average, by three notches and, similar to Alp (2013), that stringency increased dramatically from 2002 to 2009. As both Alp (2013) and Baghai et al. (2014) indicate, what remains unanswered is *why* credit ratings have become more stringent and why some firms are affected more than others.

We predict that greater issuer business press coverage over time is partially responsible for the stricter rating standards due to the greater information dissemination, criticism, and discovery of rating failures that can impose reputational penalties on the rating agencies. Concurrent with the growing stringency in credit rating standards, the development of new technologies, new media outlets, alternative news sources, and increased competition for traditional media outlets have led to more press coverage with greater dissemination (Wall 2005; Nguyen 2008; Lewis and Cushion 2009; Mitchelstein and Boczkowski 2009; Tetlock 2010; Saltzis 2012; Drok and Hermans 2016). As shown in Figure 1, the median number of annual news stories for firms with public credit ratings increased substantially from 2001 to 2011. This growth in coverage is expected to increase the prominence and visibility of certain issuers, creating greater reputational risk for the credit rating agencies covering these issuers. This leads us to our last research hypothesis:

H3: Increased business press coverage of issuers is a mediating factor for the stricter credit rating standards observed since 2002.

III. RESEARCH DESIGN

Business Press Coverage and Rating Timeliness

Days Between Downgrade and Default

We begin by investigating how business press coverage affects the timeliness of credit ratings prior to default. We measure business press coverage, *LCover,* as the natural logarithm of 1 plus the number of articles written about a firm during the six months ending one year before a default date. This analysis is of particular relevance given the high visibility of defaults and the relatively high reputational harm to rating agencies for "missing" or "delaying" a downgrade for such issuers. We investigate this issue by estimating an ordinary least squares (OLS) regression focused on the number of days between default and downgrades issued within the year prior to default. In this analysis, *Days* is the number of days between the downgrade of the bond to BB/Ba or lower (i.e., the downgrade is to speculative grade) and the default date (maximum value of 0, minimum value of -360). We code the number of days prior to default that a rating agency downgrades the bond, *Days,* lower (i.e., a more negative number of days) for more timely ratings. If the credit rating agencies release more timely (i.e., earlier) downgrades in advance of defaults for issuers with greater business press coverage, then we expect the coefficient for *LCover* to be negative.

We include control variables to capture cross-sectional differences in issuers and debt issues. Specifically, our control variables for the timeliness of credit ratings, similar to those used in Cheng and Neamtiu (2009) and Bonsall (2014), include *SPRating, FitchRating, Bankruptcy, LAsset, IntCover, DebtEquity, LFace, AssetBacked, Convertible, Senior, Enhance, Put, Redeem, Maturity, Rating, GDP, CRSPBond, SP500,* and *LDefaults* (see Appendix A for variable definitions). Our control variables for the determinants of business press coverage, which represent potential competing explanations for our findings, are similar to those used in Fang and Peress (2009), Bushee et al. (2010), and Hillert et al. (2014), and include *LMktCap, BM, LFollow, InstHold, IVol, Ret, SP500Member, LEmployee, LOwn, NASDAQTraded, Turnover,* and *MomStrength*. Of particular note, *Ret* controls for differences in news across issuers, which could result in differential coverage by the business press.[9] To further limit the possible influence of omitted variables on our findings, we use two measures of how busy the business press is with other news as instruments for business press coverage and alternatively estimate our primary analyses using two-stage

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[8] Earlier research documents a movement by the major credit rating agencies to stricter rating standards prior to 2002. Blume et al. (1998) show that during the period from 1978–1995, firms with consistent financial ratios receive less favorable credit ratings, on average, in later years. Jorion et al. (2009), examining a similar time period, document that only investment-grade firms appear to exhibit increasing stringency in their credit ratings and that the increase is attributable to changes in the importance of accounting-based variables to credit ratings.

[9] Although we control for the content of the information contemporaneously released by the business press using stock market returns, similar to Fang et al. (2014) and Hillert et al. (2014), we do not expect that the business press is a primary source of information for the credit rating agencies due to the rating agencies having access to material nonpublic information. In a private conversation, a senior-level employee at one of the major credit rating agencies indicated that credit rating analysts are firm insiders, always aware of developments before they are publicly announced by the issuer. For instance, an issuer may seek advice about how a planned merger or debt issuance would affect its credit rating.

least squares. Details of the approach and the empirical results are available in the Online Appendix (see Appendix B for the link to the downloadable document); our later inferences are unchanged when using this alternative approach.

Possible reverse causality is limited through our choice of measurement periods for our variable of interest and control variables. The coverage and return variables are measured over the six months occurring one year prior to a default date. In later tests, the variables are measured over the six months occurring one year prior to a default date, non-default date (defined later), or fiscal year-end.[10] Despite being measured one year prior, our coverage measure is a reasonable measure of business press coverage at defaults and downgrades. In untabulated analyses, we find that the pairwise correlations among the lagged coverage measure and coverage during the two-week window surrounding defaults and downgrades are 77 and 69 percent, respectively. We measure the other control variables in the quarter ending one year before the default date.

Weighted Average Rating Before Default

To further investigate how business press coverage affects the timeliness of credit ratings before default, we also estimate an OLS regression focused on the average rating in the year prior to default. In this analysis, $\overline{Rating}$ is the average credit rating over the year prior to the default date (weighted by the number of days each rating was outstanding). We code $\overline{Rating}$ as higher for ratings closer to default (i.e., AAA/Aaa = 1, C/C = 21). If credit rating agencies issue more timely ratings in advance of default for issuers with greater business press coverage, then we expect the coefficient for *LCover* to be positive. The control variables are the same as those used in the analysis of *Days,* with the exception of the exclusion of *Rating.* Unlike *Days,* $\overline{Rating}$ captures how closely (in magnitude) outstanding ratings are to the lowest rating category in the year prior to the default date. Accordingly, $\overline{Rating}$, while capturing rating timeliness, also provides some evidence regarding the relative accuracy of the rating agencies (i.e., agencies would obtain greater accuracy by rating defaulting bonds at lower rating levels in the year preceding the default event).

Business Press Coverage and Rating Accuracy

Type I Rating Errors

We start our investigation of rating accuracy by testing whether the credit rating agencies alter accuracy for defaulting issuers. We estimate a probit regression model with the dependent variable E_{TypeI}, which captures the rating agencies' ability to avoid missing issuer defaults (i.e., Type I errors). The dichotomous variable is set equal to 1 if a bond possesses a credit rating of B−/B3 or more favorable one year before a default event, and 0 otherwise. We measure rating agency errors relative to the edge of the B and CCC broad rating categories. That is, Type I errors (i.e., overly optimistic ratings) occur when issuers experience a default event within one year of the rating date that have an outstanding rating of B−/B3 or more favorable. In the period prior to default, a Type I error occurs if ratings fail to anticipate the upcoming default. Our controls follow those used in prior credit rating studies investigating Type I errors (e.g., Cheng and Neamtiu 2009; Bonsall 2014) and those used in prior business press studies (e.g., Fang and Peress 2009; Bushee et al. 2010; Hillert et al. 2014).

Type II Rating Errors

We next examine whether credit rating agencies change rating accuracy for non-defaulting issuers. Specifically, we estimate a probit model with the dependent variable E_{TypeII}, which captures the rating agencies' ability to avoid providing false warnings regarding issuer defaults (i.e., Type II errors). The dichotomous variable is set equal to 1 if a bond possesses a credit rating of CCC+/Caa1 or less favorable one year before a non-default event, and 0 otherwise. Similar to our investigation of Type I errors, we measure rating agency errors relative to the edge of the B and CCC broad rating categories. That is, Type II errors (i.e., overly pessimistic ratings) occur when issuers do not experience a default event within one year of the rating date and have an outstanding rating of CCC+/Caa1 or less favorable at the rating date. Control variables follow those used by Cheng and Neamtiu (2009), Fang and Peress (2009), Bushee et al. (2010), Bonsall (2014), and Hillert et al. (2014).

Rating Stringency Over Time

The final aspect of rating accuracy we explore is rating stringency. We assess rating stringency following the year indicator variable approach of Blume et al. (1998), Alp (2013), and Baghai et al. (2014). The dependent variable is *Rating,* defined as the S&P long-term issuer-level credit rating for firm *i* three months after the end of fiscal year *t*.[11] We assess rating stringency relative to 2001 by excluding the year indicator variable for 2001. Evidence of increased rating stringency is

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[10] The Online Appendix provides greater discussion of how *LCover* is constructed for each primary test.

[11] Prior rating stringency studies do not focus on Moody's and Fitch ratings due to their ratings including recovery rate information, as well as default risk information.

indicated by positive coefficients for the year indicator variables in an ordered logit regression model of ratings. While related to our $\overline{Rating}$ and Type I error investigations, this analysis differs in that it explores rating stringency for all issuers, not just those defaulting.

We investigate whether greater business press coverage leads to more stringent credit rating standards using a mediation (i.e., path analysis) design (MacKinnon 2008). Our analysis tests whether business press coverage, the mediator variable, is an important mechanism underlying the association between time since 2001 and rating stringency. We expect that the growth in business press coverage since 2001, as shown in Figure 1, is an important driver of greater stringency in ratings. Using a structural equation model (SEM), the mediation effect is measured as the reduction in the coefficients on the year indicator variables when business press coverage is included as a mediator variable (MacKinnon and Dwyer 1993). We begin by estimating the year indicator variable coefficients, λ_t, using:

$$Rating_{it} = \mu_1 + \lambda_t + \theta_t Controls_{it} + \varepsilon_{1,it} \tag{1}$$

excluding a year indicator variable for 2001. We then modify Equation (1) to include our business press coverage variable, *LCover,* now measured during the six months ending one year before the fiscal year-end, to estimate the mediating effect of issuer coverage on credit rating standards:

$$Rating_{it} = \mu_2 + \lambda'_t + \beta LCover_{it} + \theta_t Controls_{it} + \varepsilon_{2,it} \tag{2}$$

and also estimate the relation of the year indicator variables, α_t, on *LCover* using:

$$LCover_{it} = \mu_3 + \alpha_t + \theta_t Controls_{it} + \varepsilon_{3,it} \tag{3}$$

The year indicator variable coefficients, λ_t, in Equation (1) represent the total effect of rating stringency relative to the benchmark year 2001. The mediated effect (i.e., the indirect effect) is represented by the sum of $\lambda_t - \lambda'_t$ for all t from Equations (1) and (2) or, alternatively, by the sum of $\alpha_t * \beta$ for all t in Equations (3) and (2). We test for an overall mediation affect using a joint F-test for the differences in the sum of $\lambda_t - \lambda'_t$ for all t. The sum of the year indicator variable coefficients, λ'_t, represents the effect of rating stringency since 2001 after mediation (i.e., the direct effect). The explanatory variables used to model credit ratings are those used in Baghai et al. (2014), which are based on prior related research and industry practice. These variables include *IntCov, Profit, Book_Lev, Debt/EBITDA, Neg.Debt/EBITDA, Vol, Cash/Assets, ConvDe/Assets, Rent/Assets, PPE/Assets, CAPEX/Assets, Beta,* and *Idio.Risk,* as well as industry fixed effects using three-digit SIC codes. We also include the previously used control variables for business press coverage.

IV. SAMPLE AND DESCRIPTIVE STATISTICS

Sample Selection

Our sample selection begins with all corporate bonds and their related ratings available from the Mergent Fixed Income Securities Database (FISD) during the period June 2000 through December 2011. We collect bond-level characteristics, default events, and ratings from S&P, Moody's, and Fitch (i.e., the major credit rating agencies) from the Mergent Fixed Income Securities Database. We collect issuer-level characteristics from Compustat and obtain stock price information from CRSP. Consistent with prior studies, we exclude financial firms (SIC 6000–6999) from the sample. We restrict the sample to include only firms with both book value of assets and sales above $1 million. Also, to limit the influence of outliers, we winsorize all continuous variables at the top and bottom 1 percent.

We merge issuer-level news data provided by RavenPack in its 2012 Dow Jones Edition of news coverage to the bond and issuer data. RavenPack provides news data analytics from the Dow Jones Newswire service beginning in January 2000.[12] Accordingly, our final sample begins in 2000 and ends in 2011. There are approximately ten million unique news stories in the RavenPack data, covering just over 8,000 companies during the sample period.[13] In assigning a news story to a company,

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[12] The Dow Jones Edition includes stories from Dow Jones Newswires and other Dow Jones news products (e.g., *Barron's* and the *Wall Street Journal*). We use this source as Dow Jones articles have commonly been investigated in prior research investigating the business press (e.g., Tetlock 2010; Engelberg, Reed, and Ringgenberg 2012; Drake et al. 2014). We also use this source as it allows us to begin our sample period in 2000. Recently, RavenPack has made available a more comprehensive news database that, in addition to the Dow Jones News Service sources, covers stories across approximately 20,000 online news sources, including Reuters, Bloomberg, NBC, ABC, CBS, Fox, CNN, CNBC, Yahoo!, and Morningstar.com since January 2007. The overlap between these two different sources of news coverage is very high. Specifically, using six-month windows and all stories with relevance scores (defined below) of 75 and above from the major news sources or, alternatively, using lower relevance score cutoffs, pairwise correlations between the two coverage measures exceed 90 percent.

[13] The news database adds a new observation for every company identified in a news story. Therefore, there are approximately 20 million observations in the database.

RavenPack records a measure, Relevance, that indicates the prominence that a particular company plays in a news story, with higher values corresponding to greater prominence in a story.[14] Our measure of news coverage from the RavenPack database is a count of news stories with relevance scores greater than 20 for each issuer in each period in which an issuer's name can be identified somewhere in the story.[15]

We also merge individual analyst characteristic data provided by the authors of Fracassi et al. (2016). Using credit reports from the S&P Global Credit Portal (S&P Global Ratings 2017), the Moody's website, and the Fitch ratings website, individual credit analyst names and report announcement dates are combined with analyst demographic data from web searches (e.g., LinkedIn profiles). As Fracassi et al. (2016) discuss in greater detail, educational, biological, and employment data are collected for 638 unique analysts. For each analyst, this information includes school, degree, degree data, gender and age, tenure (firm, industry, and agency), and number of firms currently covered. The position of each analyst (e.g., Vice President or Senior Analyst) is not collected, as only Moody's consistently identifies the titles of its analysts. The data for each issuer are averaged across analysts for each firm-quarter. Analyst-issuer matches are relatively stable over time, suggesting that there are costs associated with severing such ties. Detailed information about each dataset and descriptive statistics are provided in the Online Appendix.

V. EMPIRICAL RESULTS

Business Press Coverage and Rating Downgrade Timeliness

Days Between Downgrade and Default

Table 1 provides our empirical results for *Days*. We report t-statistics based on standard errors clustered two-way by firm and quarter. In column (1), we find that the coefficient for *LCover* is statistically negative. The estimated coefficient on *LCover* implies that an interquartile range increase (i.e., an increase from the 25th to 75th percentile) in *LCover* is associated with downgrades in advance of defaults approximately 39 trading days earlier (untabulated).[16] This evidence indicates that credit rating agencies issue ratings earlier for more widely covered issuers that eventually default.[17]

Broad business press coverage could inadvertently lead to greater observed rating pessimism because of the business press bias to cover negative news stories (e.g., Gurun and Butler 2012). This could lead to issuers with greater business press coverage having more negative new stories and more timely ratings. We explore the importance of this possibility by including an additional variable, *LCover$_{Neg}$*, which is the natural logarithm of 1 plus the number of negative sentiment articles written about a firm during the six months ending one year before a default date and, in later tests, non-default date, or fiscal year-end.[18] In column (3) of Table 1, we find that the coefficient for *LCover* is statistically negative and of similar magnitude. In addition, we find that the coefficient for *LCover$_{Neg}$* is insignificant. Thus, we fail to find evidence that negative sentiment stories are more important than other stories in explaining default downgrade timeliness.

The prominence and quality of the media outlet could lead to business press coverage having a greater effect on the reputation risk faced by the credit rating agencies. To investigate this possibility, we include an additional variable, *LCover$_{WSJ}$*, which is the natural logarithm of 1 plus the number of articles written about a firm in the *Wall Street Journal* during the six months ending one year before a default date and, in later tests, non-default date, or fiscal year-end. We focus on the *WSJ* due to its large and public audience relative to other outlets. In addition, we focus on the *WSJ* due its perceived high quality of news

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[14] Relevance scores range from 0 to 100. Relevance scores of 75 and above are assigned when the firm's name is identified in the first paragraph of a story. A relevance score of 20 is assigned in special cases where firm names are identified, but are not necessarily relevant to the story, such as when a news story about IBM (a high-relevance score firm) mentions a rating by Moody's (relevance score = 20). Because stories with scores of 20 or below do not immediately apply to the subject of the story, we do not count these stories in our measure of business press coverage. However, the pairwise correlations among counts of all news stories, only high-relevance news stories, and only low-relevance news stories are all in excess of 90 percent.

[15] As an alternative, we use only those stories with relevance scores of 75 and above (i.e., those stories where the firm name is either in the headline or first paragraph of the story). In untabulated tests, we find that this alternative measure is very similar to the one used in our primary tests; the correlation between the two measures is 97 percent.

[16] We examine interquartile range differences to provide cross-sectional comparisons of firms with varying levels of business press coverage, not as an indication of a typical change in business press coverage, which does not vary much over time (e.g., over a three-year period, we only observe 2 percent of our sample firms with that large of a change).

[17] We also examine the possibility of credit rating agencies being less willing to maintain optimistic ratings when press coverage is high. This is tested by including an additional variable for the interaction of *Rating* with *LCover*. In untabulated tests, we find that downgrades are even more likely for bonds with optimistic ratings when press coverage is high.

[18] *LCover$_{Neg}$* includes stories when the issuer is identified in a headline (i.e., RavenPack relevance score of greater than or equal to 90) and the net sentiment of the story is negative (i.e., RavenPack CSS less than 50. CSS is RavenPack's textual sentiment score, ranging from 0 to 100, with higher values representing text with more positive language and 50 representing a neutral textual tone). We use a higher relevance score to ensure that the negative sentiment story is about the issuer rather than other companies.

TABLE 1

Business Press Coverage and Downgrade Timeliness before Default

	Days (1) Baseline	$\overline{Rating}$ (2) Baseline	*Days* (3) Negative Stories	$\overline{Rating}$ (4) Negative Stories	*Days* (5) WSJ Stories	$\overline{Rating}$ (6) WSJ Stories
LCover	−13.0308***	0.2905***	−11.6308***	0.3174***	−8.6771*	0.1405
	(−3.64)	(2.69)	(−3.14)	(2.85)	(−1.73)	(1.32)
$LCover_{Neg}$			1.5035	−0.0564		
			(0.08)	(−0.15)		
$LCover_{WSJ}$					−36.5912**	0.5912***
					(−2.27)	(2.82)
Rating Timeliness Controls						
SP Rating	−16.8676**	−0.2611	−17.1456**	−0.2294	−18.3236*	−0.2494
	(−2.21)	(−1.18)	(−2.23)	(−1.06)	(−1.95)	(−1.23)
FitchRating	−12.8388***	0.7303***	−13.0811***	0.7186***	−10.8275	0.7258***
	(−3.15)	(4.25)	(−3.19)	(4.23)	(−1.60)	(3.99)
Bankruptcy	−45.3427	0.7860	−45.5458	0.7112	−43.1025	1.0788
	(−1.39)	(0.96)	(−1.37)	(0.89)	(−1.31)	(1.34)
LAsset	12.5484	1.8030***	14.6545	1.7720***	−3.9023	1.5040***
	(1.09)	(5.67)	(1.32)	(5.60)	(−0.34)	(5.02)
IntCover	−0.8028	−0.0599**	−0.7880	−0.0615**	−0.4723	−0.0661**
	(−0.62)	(−2.16)	(−0.62)	(−2.25)	(−0.41)	(−2.32)
DebtEquity	−3.8138*	0.1055**	−3.8249*	0.1036**	−3.7165**	0.1177***
	(−1.70)	(2.44)	(−1.70)	(2.42)	(−2.25)	(3.30)
LFace	0.6387	−0.0607*	0.6334	−0.0623*	1.3219*	−0.0383
	(1.20)	(−1.83)	(1.22)	(−1.84)	(1.92)	(−1.48)
AssetBacked	9.9066	1.4009	8.1966	1.4983	−32.4881	0.6953
	(0.25)	(1.37)	(0.21)	(1.59)	(−0.91)	(0.59)
Convertible	7.4343	−0.2466	7.9732	−0.2627	6.9148	−0.2137
	(0.58)	(−0.60)	(0.62)	(−0.64)	(0.50)	(−0.52)
Senior	−5.9176	0.4210	−8.7426	0.5356	8.6815	0.6612
	(−0.28)	(0.70)	(−0.44)	(0.89)	(0.33)	(1.07)
Enhance	1.8881	0.1845	3.6782	0.1357	−0.7737	0.1548
	(0.12)	(0.43)	(0.23)	(0.32)	(−0.05)	(0.36)
Put	5.9239	−0.1538	6.0958	−0.1238	1.2168	−0.2496
	(0.55)	(−0.51)	(0.57)	(−0.41)	(0.12)	(−0.84)
Redeem	1.3602	−0.1440	1.6163	−0.1598	2.6259	−0.1397
	(0.43)	(−0.90)	(0.51)	(−0.99)	(0.79)	(−0.96)
Maturity	−0.0863	−0.0014	−0.1285	0.0003	0.0305	0.0004
	(−0.29)	(−0.14)	(−0.43)	(0.03)	(0.11)	(0.05)
Rating	9.9428***		10.1690***		10.8383***	
	(5.19)		(5.42)		(5.82)	
GDP	−0.0038	−0.0002	−0.0042	−0.0002	−0.0043	−0.0002
	(−0.38)	(−1.33)	(−0.42)	(−1.41)	(−0.51)	(−1.34)
CRSPBond	−194.9714**	−0.8568	−187.5843**	−1.5896	−236.6831***	−0.8540
	(−2.29)	(−0.46)	(−2.21)	(−0.88)	(−2.65)	(−0.46)
SP500	−0.1339**	0.0013	−0.1333**	0.0009	−0.1254**	0.0018
	(−2.02)	(0.96)	(−2.01)	(0.67)	(−2.28)	(1.39)
LDefaults	−0.0627**	0.0007	−0.0606**	0.0005	−0.0598**	0.0008**
	(−2.38)	(1.55)	(−2.27)	(1.13)	(−2.06)	(1.98)
Coverage Controls						
LMktCap	−21.1325**	−0.4760**	−21.7997**	−0.4683*	−17.9953*	−0.3991*
	(−2.15)	(−1.99)	(−2.20)	(−1.94)	(−1.79)	(−1.74)
BM	3.2091	−0.3574	3.3548	−0.3607	6.3792	−0.3802
	(0.34)	(−1.34)	(0.36)	(−1.34)	(0.70)	(−1.50)

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TABLE 1 (continued)

	Days (1) Baseline	$\overline{Rating}$ (2) Baseline	Days (3) Negative Stories	$\overline{Rating}$ (4) Negative Stories	Days (5) WSJ Stories	$\overline{Rating}$ (6) WSJ Stories
LFollow	5.5174***	0.0483*	5.6036***	0.0416	4.5342***	0.0402
	(2.85)	(1.74)	(2.91)	(1.53)	(2.69)	(1.53)
InstHold	−134.7385***	−3.1580***	−135.3998***	−3.1100***	−120.3182***	−2.7931***
	(−3.22)	(−3.00)	(−3.27)	(−2.95)	(−3.03)	(−2.71)
IVol	−119.8930**	−1.0314	−116.3123**	−1.3480	−119.8459***	−0.7553
	(−2.54)	(−0.85)	(−2.52)	(−1.10)	(−2.71)	(−0.61)
Ret	−17.8100	0.7655***	−18.0480	0.7391***	−27.4035**	0.8323***
	(−1.21)	(2.81)	(−1.23)	(2.68)	(−2.02)	(3.18)
SP500Member	−2.3139	−0.7753	−1.4799	−0.8805	−6.2640	−0.9927
	(−0.06)	(−0.93)	(−0.04)	(−1.03)	(−0.17)	(−1.17)
LEmployee	30.7109***	−0.3117	30.1870***	−0.3175	28.0904***	−0.3225
	(3.03)	(−1.49)	(2.95)	(−1.52)	(3.00)	(−1.63)
LOwn	−39.3307***	−0.2741	−39.6476***	−0.2445	−31.7276***	−0.2105
	(−3.91)	(−1.30)	(−3.94)	(−1.14)	(−4.32)	(−1.05)
NASDAQTraded	29.8134	−0.8516	33.7029	−0.9591	33.4773	−0.9732
	(1.17)	(−1.46)	(1.25)	(−1.61)	(1.36)	(−1.62)
Turnover	2659.7358**	−175.6437***	2594.5714*	−168.5588***	3630.2909***	−175.2678***
	(1.98)	(−6.49)	(1.92)	(−5.93)	(3.55)	(−7.16)
MomStrength	−6.7990	0.2368	−6.4430	0.2400	−10.4485	0.1339
	(−0.53)	(0.81)	(−0.50)	(0.84)	(−0.83)	(0.46)
Constant	101.9379	−1.2250	88.8443	−0.0769	206.4018*	−0.2774
	(0.70)	(−0.40)	(0.60)	(−0.03)	(1.76)	(−0.09)
Observations	9,888	3,754	9,888	3,754	9,888	3,754
Adjusted R^2	0.522	0.912	0.524	0.912	0.567	0.916

*, **, *** Denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
This table presents the results of estimating OLS regressions to test the association between business press coverage and credit rating timeliness in advance of default events. The dependent variable in columns (1), (3), and (5) is *Days:* the number of days between the downgrade of the bond to BB/Ba or lower (i.e., the downgrade is to speculative grade) and the default date (maximum value of 0, minimum value of −360); and in columns (2), (4), and (6) is $\overline{Rating}$: the average credit rating over the year prior to the default date (weighted by the number of days each rating was outstanding). Ratings are coded higher when closer to default (i.e., AAA/Aaa = 1, C/C = 21). *LCover, LCover$_{Neg}$*, and *LCover$_{WSJ}$* are the natural logarithm of 1 plus the number of articles, negative sentiment articles, and articles published in the *Wall Street Journal* written about a firm during the six months ending one year before a default date, respectively. Standard errors are clustered two-way by firm and quarter.
Variable definitions are presented in Appendix A.

coverage. Column (5) of Table 1 indicates that *LCover* and *LCover$_{WSJ}$* are significantly negative. This provides evidence that coverage by the *WSJ* has a greater effect on the timeliness of ratings, as captured by *Days*.

Weighted Average Rating Before Default

Table 1 presents our results for $\overline{Rating}$. We report t-statistics based on standard errors clustered two-way by firm and quarter. In column (2), we find that the coefficient for *LCover* is statistically positive. The coefficient of 0.2905 implies than an interquartile range increase in *LCover* is associated with average ratings in the year prior to a default that are lower by approximately 0.91 notches. We again investigate the importance of negative news stories on our findings by separately including *LCover$_{Neg}$*. In column (4), we find that the coefficient for *LCover$_{Neg}$* is insignificant. Again, we fail to find evidence consistent with negative sentiment stories being more important than other stories in explaining default rating timeliness. We also again investigate the importance of the outlet on our findings by separately including *LCover$_{WSJ}$*. In column (6), we find that *LCover* is insignificant and *LCover$_{WSJ}$* is significantly positive, indicating that *WSJ* coverage is more important than coverage by other outlets.

In sum, for defaulting issuers, our empirical evidence indicates that rating agencies provide more timely rating actions for issuers with greater business press coverage, consistent with H1. Specifically, our findings suggest that rating agencies issue downgrades earlier for such issuers. In addition, our findings suggest that rating agencies maintain lower ratings in the year

prior to default for such issuers. These findings are stronger when the outlet is of greater prominence and higher quality. We next examine whether the accuracy aspect of credit ratings differs for more widely covered issuers.

Business Press Coverage and Credit Rating Accuracy

Type I Rating Errors

Table 2 provides our empirical findings for E_{TypeI}. In the probit regression estimation, presented in column (1), the coefficient for *LCover* is significantly negative. In terms of marginal effects (untabulated), an interquartile range increase in *LCover* implies a decrease in the probability of the rating agencies committing a Type I error by 847 basis points, which represents a 12 percent decline relative to the frequency of Type I errors when we hold *LCover* at its mean value. This evidence is consistent with the rating agencies reducing Type I errors for issuers with greater business press coverage.

Similar to our timeliness analysis, a greater number of negative news stories, which are associated with issuers with greater coverage, could capture other unintended aspects of business press coverage on Type I errors. Specifically, a greater number of negative news stories could lead to more pessimistic news stories prior to default and, accordingly, lower Type I errors. We again separately include $LCover_{Neg}$ to explore the importance of this possibility. In Table 2, column (3), we fail to find evidence that negative news stories are of relatively greater importance; the coefficient for $LCover_{Neg}$ is insignificant.

In addition, greater coverage of an issuer by the *WSJ* could pose greater reputational risk for the credit rating agencies. Because of this, greater *WSJ* coverage could lead to lower Type I errors. In column (5) of Table 2, we find that *LCover* is insignificant, while $LCover_{WSJ}$ is significantly negative. This suggests that the standing of the news outlet matters for how business press coverage affects credit rating agencies' decisions to issue more accurate ratings.

Type II Rating Errors

Table 2 also provides our empirical findings for Type II errors, E_{TypeII}. In column (2), in our probit regression, we find that the coefficient for *LCover* is significantly negative. In terms of marginal effects (untabulated), an interquartile range increase in *LCover* implies a decrease in the probability of the rating agencies committing a Type II error by 29 basis points, which represents an 86 percent decline relative to the frequency of Type II errors when *LCover* is evaluated at its mean value. We separately include $LCover_{Neg}$ in column (4) for reasons similar to those discussed above (although the greater prevalence of negative news stories should lead against finding lower Type II errors for widely covered issuers). We find that the coefficient for $LCover_{Neg}$ is insignificant, consistent with the type of sentiment in the story not being relatively more important. We also separately include $LCover_{WSJ}$ in column (6) to investigate the effect of the prominence and quality of the media outlet on Type II errors. We find that the coefficients for *LCover* and $LCover_{WSJ}$ are significantly negative, consistent with *WSJ* coverage having a greater effect on the reduction in Type II errors. This evidence suggests that rating agencies are able to reduce Type II errors for issuers that receive greater attention from the business press, especially when the outlet is of greater standing. Together with the evidence for Type I errors, these findings support H2.

Rating Stringency Over Time

For our rating stringency tests, we begin by empirically documenting changes in credit rating stringency from 2001 to 2011. The first column of Table 3 presents the ordered logit regression results using the full sample. Marginal effects are reported for interquartile range changes in continuous independent variables and one-unit changes for binary independent variables. As expected, the marginal effects for the coefficients on the year indicator variables increase from 0.2434 in 2002 to 1.1779 in 2011. Similar to the findings of Alp (2013) and Baghai et al. (2014), these results indicate that credit rating standards have become increasingly more stringent by nearly 1.2 notches over our sample period.

We also separately investigate rating stringency for issuers with investment-grade and speculative-grade ratings. This is important as the stringency of rating standards can fundamentally differ across these types of issuers. The fifth column of Table 3 presents the ordered logit results for the investment-grade subsample. For the year indicator variables, the marginal effects for the coefficients are significantly positive and increase from 0.3456 in 2002 to 1.4525 in 2011. The ninth column of Table 3 presents the ordered logit results for the speculative-grade subsample. For the year indicator variables, the marginal effects for the coefficients for the years after 2004 are significantly positive. The coefficients grow from 0.0219 in 2002 to 1.8235 in 2008 and then decline to 0.9432 in 2011. Taken together, these results indicate that increased rating stringency exists for both issuers with investment-grade and speculative-grade ratings, but that rating stringency is more pronounced for investment-grade issuers in some years and at the end of our sample period.

In the second column of Table 3, we present the results of our mediation analysis for the full sample, which adds *LCover* as a mediating variable. The coefficient estimate for *LCover* is significantly positive, indicating that more widely covered issuers receive more stringent ratings. The marginal effect of 1.0456 indicates that an interquartile range increase in *LCover* is

TABLE 2
Business Press Coverage and Credit Rating Accuracy

	E_{TypeI} (1) Baseline	E_{TypeII} (2) Baseline	E_{TypeI} (3) Negative Stories	E_{TypeII} (4) Negative Stories	E_{TypeI} (5) WSJ Stories	E_{TypeII} (6) WSJ Stories
LCover	−0.2486***	−0.1577***	−0.2076***	−0.0822***	−0.0822	−0.0348*
	(−4.96)	(−7.03)	(−4.04)	(−3.80)	(−1.46)	(−1.69)
LCover_Neg			−0.0517	0.0179		
			(−0.22)	(0.23)		
LCover_WSJ					−0.7736***	−0.2713***
					(−5.50)	(−5.65)
Rating Accuracy Controls						
SP Rating	0.1985**	−0.1022***	0.2406***	−0.1035***	0.2622***	−0.1047***
	(2.17)	(−3.38)	(2.61)	(−3.41)	(2.73)	(−3.34)
FitchRating	0.5444***	−0.2364***	0.5283***	−0.2336***	0.5139***	−0.2338***
	(3.00)	(−2.89)	(2.93)	(−2.88)	(2.66)	(−2.73)
LAsset	0.6262***	−0.0243	0.6113***	−0.0268	0.7579***	−0.0663
	(4.56)	(−0.54)	(4.35)	(−0.62)	(5.57)	(−1.63)
DebtEquity	0.0562***	−0.0156***	0.0585***	−0.0149***	0.0644***	−0.0129***
	(3.82)	(−3.47)	(3.85)	(−3.54)	(4.05)	(−3.73)
LargeLoss	−0.0842	0.2210	−0.0578	0.2526*	0.0392	0.2898**
	(−0.20)	(1.48)	(−0.14)	(1.83)	(0.08)	(2.45)
NegRetain	−0.7581***	0.8688***	−0.7905***	0.8515***	−0.5813**	0.8065***
	(−2.67)	(8.30)	(−2.73)	(8.35)	(−2.23)	(8.71)
AssetBacked	0.2185	−0.0578	0.1537	0.0423	0.8759	−0.3114
	(0.28)	(−0.12)	(0.20)	(0.09)	(1.28)	(−0.68)
Convertible	−0.7809***	0.4632***	−0.7640***	0.4874***	−0.9194***	0.4846***
	(−3.03)	(4.51)	(−2.98)	(4.83)	(−2.94)	(4.81)
Senior	0.9453**	0.0924	0.8922**	0.0963	1.0017***	0.1325
	(2.28)	(0.50)	(2.23)	(0.53)	(2.94)	(0.68)
Enhance	0.1934	0.1100	0.1369	0.1213*	0.1310	0.1338**
	(1.07)	(1.56)	(0.76)	(1.78)	(0.71)	(1.99)
Put	0.1057	−0.2085	0.0867	−0.2125	0.3768	−0.2094
	(0.36)	(−1.49)	(0.30)	(−1.52)	(1.06)	(−1.45)
Redeem	0.1617	−0.0086	0.1191	−0.0144	0.0117	−0.0012
	(0.96)	(−0.06)	(0.75)	(−0.11)	(0.07)	(−0.01)
Maturity	0.0241**	0.0039	0.0272**	0.0044	0.0246**	0.0043
	(2.15)	(0.63)	(2.44)	(0.71)	(2.13)	(0.70)
GDP	−0.0001	0.0001*	−0.0001	0.0001**	−0.0002**	0.0001**
	(−0.77)	(1.85)	(−0.92)	(2.03)	(−2.48)	(2.27)
CRSPBond	−0.0519	0.2397*	−0.1104	0.2232*	−1.6944	0.2501
	(−0.04)	(1.68)	(−0.07)	(1.65)	(−1.38)	(1.54)
SP500	0.0018**	−0.0006***	0.0016**	−0.0006***	0.0016**	−0.0004**
	(2.51)	(−2.95)	(2.25)	(−3.09)	(2.25)	(−2.40)
LDefaults	0.0035	0.0015*	0.0028	0.0012*	0.0018	0.0012
	(1.36)	(1.83)	(1.12)	(1.67)	(0.77)	(1.58)
Coverage Controls						
LMktCap	−0.1508	−0.0948**	−0.1390	−0.0861**	−0.2383*	−0.0915**
	(−1.10)	(−2.03)	(−0.99)	(−2.06)	(−1.77)	(−2.51)
BM	0.1034	−0.1211**	0.0754	−0.1078**	0.0835	−0.0943*
	(0.80)	(−2.04)	(0.60)	(−2.03)	(0.62)	(−1.90)
LFollow	0.0044	−0.0047	0.0005	−0.0042	−0.0052	−0.0062
	(0.30)	(−1.00)	(0.04)	(−0.89)	(−0.39)	(−1.42)
InstHold	0.4465	0.0369	0.4716	0.0510	0.5500	0.2311
	(0.81)	(0.19)	(0.86)	(0.27)	(1.00)	(1.13)

TABLE 2 (continued)

	E_{TypeI} (1) Baseline	E_{TypeII} (2) Baseline	E_{TypeI} (3) Negative Stories	E_{TypeII} (4) Negative Stories	E_{TypeI} (5) WSJ Stories	E_{TypeII} (6) WSJ Stories
IVol	0.3129	0.6221***	0.3910	0.6625***	−0.3375	0.6995***
	(0.46)	(4.62)	(0.57)	(4.62)	(−0.50)	(5.28)
Ret	0.2884	−0.1038**	0.3215*	−0.1034**	0.3556**	−0.1157***
	(1.54)	(−2.45)	(1.76)	(−2.48)	(2.10)	(−2.94)
SP500Member	−0.2342	−0.4182***	−0.2212	−0.4550***	0.2871	−0.4543***
	(−0.49)	(−3.11)	(−0.47)	(−3.36)	(0.56)	(−3.28)
LEmployee	0.0946	0.0968**	0.1079	0.0867**	0.2085*	0.0537
	(0.91)	(2.41)	(1.05)	(2.16)	(1.90)	(1.37)
LOwn	0.0875	−0.0670**	0.0691	−0.0684**	0.0372	−0.0716***
	(0.78)	(−2.47)	(0.63)	(−2.54)	(0.32)	(−2.65)
NASDAQTraded	0.4523	0.2512**	0.3050	0.2820**	0.0908	0.2615**
	(1.60)	(2.21)	(1.10)	(2.54)	(0.33)	(2.39)
Turnover	−62.0635***	15.5220**	−56.6740***	13.6670***	−53.7847***	7.6767
	(−3.12)	(2.56)	(−3.16)	(2.58)	(−3.20)	(1.56)
MomStrength	−0.3901*	0.0520	−0.3843	0.0511	−0.2754	0.0464
	(−1.65)	(0.82)	(−1.63)	(0.77)	(−1.27)	(0.68)
Constant	−5.3339**	−1.8723***	−4.7084**	−1.9484***	−3.3190*	−1.6842***
	(−2.57)	(−3.83)	(−2.30)	(−3.97)	(−1.83)	(−3.33)
Observations	3,461	484,482	3,461	484,482	3,461	484,482
Pseudo R^2	0.593	0.363	0.598	0.368	0.644	0.382

*, **, *** Denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
This table presents the results of estimating probit regressions to test the association between business press coverage and the accuracy of credit ratings in advance of default and non-default events. Columns (1), (3), and (5) report estimates for the default sample model, in which the dependent variable is E_{TypeI}, an indicator variable set equal to 1 if a bond possesses a credit rating of B−/B3 or less favorable one year before a default event, and 0 otherwise. Columns (2), (4), and (6) report the estimates for the non-default sample model, in which the dependent variable is E_{TypeII}, an indicator variable set equal to 1 if a bond possesses a credit rating of CCC+/Caa1 or less favorable one year before a non-default event, and 0 otherwise. *LCover, LCover$_{Neg}$,* and *LCover$_{WSJ}$* are the natural logarithm of 1 plus the number of articles, negative sentiment articles, and articles published in the *Wall Street Journal* written about a firm during the six months ending one year before a default date or a non-default date, respectively. Standard errors are clustered two-way by firm and quarter.
Variable definitions are presented in Appendix A.

associated with a 0.65 notch worsening in a firm's credit rating. In addition, the coefficient estimates for the year indicator variables are generally much lower after the inclusion of business press. Columns (6) and (10) of Table 3 present the results for the investment-grade and speculative-grade subsamples. Similar to the full sample results, we find that *LCover* is an important determinant of rating levels and that coefficient estimates for the year indicator variables fall dramatically after *LCover* is included. The sentiment of press articles could influence these tests, as more negative articles could lead to the assignment of lower ratings. We find little evidence of such a role, however; *LCover$_{Neg}$* is insignificant in columns (3), (7), and (11). The prominence and quality of the outlet could have a greater effect on stringency. Consistent with this, we find that *LCover$_{WSJ}$* is significantly positive in columns (4) and (12) for the full and speculative-grade samples. *LCover$_{WSJ}$* is insignificant, however, in column (8) for the investment-grade sample.

Table 4 provides a more formal test of our path analysis. We report bootstrapped standard errors clustered by firm (MacKinnon, Lockwood, and Williams 2004). As shown for the mediated path, the path from the year indicator variables (omitting the year 2001), *Year$_t$*, to *LCover* is significantly positive. Moreover, the path from *LCover* to *Rating* is significantly positive, providing evidence of more widely covered issuers receiving more stringent ratings. The product of these two path coefficients (the indirect effect) is significantly positive, consistent with H3. This indicates that business press coverage is an important channel that leads to increased stringency in credit standards since 2001. After taking into account *LCover,* the mediated coefficient (the direct effect) between *Year$_t$* and *Rating* is relatively small. Specifically, the direct effect of 0.6437 relative to the total effect of 7.5372 represents a reduction of over 90 percent. Table 4 provides the path analyses for the investment-grade and speculative-grade subsamples. The total effects and the indirect effects are significantly positive for both subsamples. As with the full sample, the mediated coefficient between *Year$_t$* and *Rating* is relatively small.

TABLE 3
The Role of Business Press Coverage in the Increasing Stringency of Credit Ratings: Ordered Logit Analysis

| | Rating: Full Sample | | | | Rating: Investment Grade | | | | Rating: Speculative Grade | | | |
| | Unmediated | Mediated with *LCover* | | | Unmediated | Mediated with *LCover* | | | Unmediated | Mediated with *LCover* | | |
	(1)	(2) Baseline	(3) Negative Stories	(4) WSJ Stories	(5)	(6) Baseline	(7) Negative Stories	(8) WSJ Stories	(9)	(10) Baseline	(11) Negative Stories	(12) WSJ Stories
LCover		1.0456*** (12.63)	1.0423*** (12.57)	1.0437*** (12.60)		1.2812*** (9.37)	1.2776*** (9.34)	1.2811*** (9.37)		0.8256*** (6.52)	0.8203*** (6.48)	0.8343*** (6.58)
LCover$_{Neg}$			−0.0536 (−1.06)				−0.0472 (−0.69)				−0.0314 (−0.46)	
LCover$_{WSJ}$				0.0825** (2.53)				0.0060 (0.10)				0.2360*** (2.95)
Rating Controls												
IntCover	−0.0121*** (−5.96)	−0.0116*** (−5.73)	−0.0117*** (−5.77)	−0.0116*** (−5.73)	−0.0132*** (−4.36)	−0.0134*** (−4.49)	−0.0135*** (−4.52)	−0.0134*** (−4.49)	−0.0030 (−1.37)	−0.0027 (−1.27)	−0.0028 (−1.32)	−0.0027 (−1.24)
Profit	−0.5585 (−1.39)	−0.6269 (−1.57)	−0.6311 (−1.58)	−0.6271 (−1.57)	−0.6854 (−1.14)	−0.6679 (−1.12)	−0.6732 (−1.12)	−0.6675 (−1.12)	−1.0709** (−2.32)	−1.1510** (−2.51)	−1.1496** (−2.51)	−1.1451** (−2.49)
Book_Lev	2.1576*** (7.45)	2.0955*** (7.18)	2.0980*** (7.19)	2.0829*** (7.14)	2.0186*** (3.31)	2.0398*** (3.33)	2.0437*** (3.34)	2.0380*** (3.33)	1.5245*** (5.35)	1.4880*** (5.21)	1.4948*** (5.24)	1.4736*** (5.18)
Debt/EBITDA	0.0423*** (4.66)	0.0395*** (4.33)	0.0396*** (4.34)	0.0392*** (4.31)	−0.0120 (−0.93)	−0.0102 (−0.81)	−0.0103 (−0.81)	−0.0102 (−0.81)	0.0715*** (7.44)	0.0696*** (7.25)	0.0699*** (7.28)	0.0698*** (7.26)
Neg.Debt/EBITDA	0.8045*** (3.48)	0.7951*** (3.43)	0.7940*** (3.43)	0.8003*** (3.45)	−0.7297** (−1.98)	−0.7114* (−1.94)	−0.7137* (−1.94)	−0.7110* (−1.93)	1.3053*** (5.02)	1.2970*** (4.99)	1.2981*** (4.99)	1.3223*** (5.07)
Vol	2.0389*** (5.23)	2.0361*** (5.25)	2.0294*** (5.24)	2.0325*** (5.26)	1.5828 (1.92)	1.5561* (1.89)	1.5537* (1.89)	1.5578* (1.89)	1.2046*** (3.40)	1.1662*** (3.30)	1.1531*** (3.26)	1.1588*** (3.29)
Cash/Assets	−0.1134 (−0.29)	0.0121 (0.03)	0.0037 (0.01)	−0.0251 (−0.06)	−0.9451 (−1.44)	−1.0120 (−1.58)	−1.0196 (−1.59)	−1.0153 (−1.59)	1.2689** (2.54)	1.3740*** (2.72)	1.3606*** (2.70)	1.2926** (2.57)
ConvDel/Assets	2.3706*** (4.34)	2.4824*** (4.58)	2.4752*** (4.57)	2.4823*** (4.59)	2.5294* (1.83)	2.4918* (1.80)	2.4933* (1.81)	2.4940* (1.81)	1.6821*** (3.02)	1.7705*** (3.23)	1.7584*** (3.21)	1.7547*** (3.20)
Rent/Assets	6.1417*** (2.84)	6.9196*** (3.31)	6.8980*** (3.30)	6.9053*** (3.31)	13.0352*** (2.88)	12.5695*** (2.82)	12.5167*** (2.81)	12.5678*** (2.82)	3.8853 (1.60)	4.5565* (1.91)	4.5155* (1.89)	4.6162* (1.94)
PPE/Assets	−0.3780 (−1.16)	−0.3291 (−1.02)	−0.3284 (−1.01)	−0.3265 (−1.01)	−0.6153 (−1.10)	−0.6652 (−1.19)	−0.6767 (−1.21)	−0.6655 (−1.19)	1.0192*** (2.87)	1.0481*** (2.97)	1.0680*** (3.03)	1.0609*** (3.00)
CAPEX/Assets	−2.8450*** (−3.21)	−2.6500*** (−3.03)	−2.6486*** (−3.03)	−2.6663*** (−3.05)	−2.9433* (−1.68)	−3.0137* (−1.72)	−2.9762* (−1.70)	−3.0113* (−1.72)	−3.2878*** (−3.31)	−3.1665*** (−3.17)	−3.1940*** (−3.21)	−3.2591*** (−3.22)
Beta	0.4702*** (6.96)	0.4667*** (6.90)	0.4684*** (6.94)	0.4688*** (6.94)	0.5113*** (4.03)	0.5103*** (4.03)	0.5129*** (4.05)	0.5104*** (4.02)	0.1384* (1.77)	0.1294* (1.66)	0.1294* (1.66)	0.1367* (1.76)
Idio.Risk	1.7915*** (21.11)	1.8013*** (21.29)	1.8012*** (21.29)	1.7870*** (21.04)	1.1627*** (6.78)	1.1622*** (6.79)	1.1608*** (6.78)	1.1608*** (6.78)	1.6951*** (18.90)	1.7108*** (19.15)	1.7124*** (19.15)	1.6809*** (18.66)
Coverage Controls												
LMktCap	−1.0335*** (−16.30)	−1.1382*** (−21.65)	−1.1396*** (−21.69)	−1.1450*** (−21.61)	−1.2630*** (−10.80)	−1.1988*** (−13.92)	−1.2003*** (−13.91)	−1.1996*** (−13.86)	−0.4814*** (−7.15)	−0.5499*** (−8.55)	−0.5502*** (−8.57)	−0.5626*** (−8.65)
BM	0.0834 (1.00)	0.0037 (0.05)	0.0023 (0.03)	0.0024 (0.03)	0.0431 (0.20)	0.1177 (0.59)	0.1140 (0.57)	0.1170 (0.59)	0.1493** (2.03)	0.1089 (1.48)	0.1072 (1.47)	0.1124 (1.53)
LFollow	0.0201*** (4.61)	0.0201*** (4.60)	0.0203*** (4.65)	0.0189*** (4.31)	0.0305*** (5.08)	0.0304*** (5.06)	0.0306*** (5.09)	0.0303*** (4.99)	−0.0083 (−1.19)	−0.0091 (−1.31)	−0.0088 (−1.27)	−0.0114* (−1.65)
InstHold	0.1115 (0.71)	0.1253 (0.80)	0.1253 (0.80)	0.1349 (0.87)	0.3477 (1.47)	0.3467 (1.47)	0.3444 (1.46)	0.3475 (1.48)	−0.4496** (−2.32)	−0.4305** (−2.23)	−0.4262** (−2.21)	−0.4172** (−2.18)
IVol	1.3282***	1.2737***	1.2667***	1.2759***	2.0205***	2.0313***	2.0221***	2.0337***	1.2583***	1.2228***	1.2173***	1.2253***

TABLE 3 (continued)

	Rating: Full Sample				Rating: Investment Grade				Rating: Speculative Grade			
	Unmediated	Mediated with *LCover*			Unmediated	Mediated with *LCover*			Unmediated	Mediated with *LCover*		
	(1)	(2) Baseline	(3) Negative Stories	(4) WSJ Stories	(5)	(6) Baseline	(7) Negative Stories	(8) WSJ Stories	(9)	(10) Baseline	(11) Negative Stories	(12) WSJ Stories
	(6.76)	(6.46)	(6.43)	(6.47)	(4.76)	(4.79)	(4.77)	(4.81)	(6.19)	(5.97)	(5.95)	(5.96)
Ret	-0.1275***	-0.1489***	-0.1489***	-0.1515***	0.0613	0.0690	0.0687	0.0692	-0.2764***	-0.2924***	-0.2913***	-0.3043***
	(-3.24)	(-3.85)	(-3.85)	(-3.91)	(0.86)	(0.96)	(0.95)	(0.96)	(-5.87)	(-6.37)	(-6.34)	(-6.59)
SP500Member	-0.2407**	-0.2353**	-0.2280**	-0.2593**	-0.2290	-0.2311	-0.2233	-0.2325	-0.1513	-0.1701	-0.1618	-0.2629
	(-2.11)	(-2.08)	(-2.01)	(-2.28)	(-1.45)	(-1.46)	(-1.40)	(-1.46)	(-0.82)	(-0.93)	(-0.89)	(-1.46)
LEmployee	-0.1358**	-0.1747***	-0.1732***	-0.1783***	-0.1142	-0.1014	-0.1006	-0.1015	-0.0997	-0.1457*	-0.1394*	-0.1588**
	(-2.51)	(-3.46)	(-3.43)	(-3.53)	(-1.48)	(-1.37)	(-1.36)	(-1.37)	(-1.19)	(-1.92)	(-1.85)	(-2.09)
LOwn	-0.0366	-0.0395	-0.0382	-0.0437*	-0.0495	-0.0487	-0.0473	-0.0490	0.0632	0.0589	0.0602	0.0558
	(-1.40)	(-1.51)	(-1.46)	(-1.67)	(-1.43)	(-1.40)	(-1.36)	(-1.42)	(1.45)	(1.35)	(1.38)	(1.28)
NASDAQTraded	-0.1562	-0.1438	-0.1441	-0.1445	-0.0330	-0.0359	-0.0364	-0.0360	0.0033	0.0208	0.0199	0.0287
	(-1.57)	(-1.46)	(-1.46)	(-1.46)	(-0.17)	(-0.19)	(-0.19)	(-0.19)	(0.03)	(0.18)	(0.17)	(0.24)
Turnover	42.3737***	41.8918***	41.9777***	41.7585***	46.9935***	47.0658***	47.1909***	47.0961***	19.5838***	18.7753***	18.8362***	17.0606***
	(7.55)	(7.45)	(7.46)	(7.44)	(4.69)	(4.70)	(4.70)	(4.71)	(2.83)	(2.74)	(2.74)	(2.54)
MomStrength	0.0525	0.0500	0.0515	0.0506	0.2340	0.2322	0.2315	0.2318	-0.0049	-0.0096	-0.0070	-0.0050
	(0.73)	(0.70)	(0.72)	(0.70)	(1.42)	(1.41)	(1.41)	(1.41)	(-0.06)	(-0.13)	(-0.09)	(-0.07)
Year												
2002	0.2434***	-0.0288	-0.0295	-0.0279	0.3456***	-0.0279	-0.0285	-0.0278	0.0219	-0.0665	-0.0676	-0.0683
	(5.67)	(-0.70)	(-0.72)	(-0.68)	(6.17)	(-0.51)	(-0.52)	(-0.50)	(0.26)	(-0.87)	(-0.88)	(-0.89)
2003	0.4148***	0.0264	0.0254	0.0277	0.5265***	0.0388	0.0378	0.0389	0.1308	-0.0289	-0.0307	-0.0279
	(8.16)	(0.61)	(0.59)	(0.64)	(7.11)	(0.66)	(0.64)	(0.66)	(1.36)	(-0.34)	(-0.36)	(-0.33)
2004	0.3621***	-0.0487	-0.0489	-0.0482	0.5451***	-0.0245	-0.0245	-0.0245	0.1226	-0.0806	-0.0810	-0.0822
	(6.26)	(-1.02)	(-1.02)	(-1.01)	(6.45)	(-0.38)	(-0.38)	(-0.38)	(1.18)	(-0.90)	(-0.91)	(-0.92)
2005	0.8880***	0.0840*	0.0835*	0.0848*	0.9411***	0.0697	0.0697	0.0698	0.8522***	0.1020	0.0996	0.1030
	(13.47)	(1.73)	(1.72)	(1.74)	(9.03)	(1.00)	(1.00)	(1.00)	(7.23)	(1.09)	(1.06)	(1.10)
2006	1.3224***	0.1895***	0.1893***	0.1912***	1.3451***	0.1642**	0.1640**	0.1645**	1.2057***	0.1874**	0.1862*	0.1900**
	(18.67)	(3.68)	(3.67)	(3.69)	(11.89)	(2.10)	(2.10)	(2.10)	(9.94)	(1.97)	(1.96)	(1.99)
2007	1.4004***	0.1772***	0.1769***	0.1792***	1.3411***	0.1219	0.1219	0.1222	1.3634***	0.2015**	0.2001**	0.2025**
	(18.25)	(3.45)	(3.45)	(3.46)	(10.80)	(1.62)	(1.62)	(1.62)	(10.58)	(2.12)	(2.10)	(2.13)
2008	1.7431***	0.2381***	0.2378***	0.2387***	1.7446***	0.1859**	0.1859**	0.1860**	1.8235***	0.2977***	0.2955***	0.2981***
	(20.63)	(4.40)	(4.39)	(4.40)	(12.50)	(2.48)	(2.48)	(2.49)	(13.14)	(2.98)	(2.94)	(2.98)
2009	1.6808***	0.2488***	0.2481***	0.2492***	1.8220***	0.2328***	0.2321***	0.2328***	1.4877***	0.2356**	0.2334**	0.2380**
	(18.53)	(4.65)	(4.62)	(4.65)	(12.12)	(2.93)	(2.92)	(2.93)	(10.71)	(2.54)	(2.50)	(2.57)
2010	0.5814***	-0.0983**	-0.0984**	-0.0979**	0.8690***	-0.0797	-0.0801	-0.0797	0.4037***	-0.0943	-0.0941	-0.0948
	(6.27)	(-2.05)	(-2.05)	(-2.04)	(6.16)	(-1.18)	(-1.19)	(-1.18)	(2.89)	(-1.12)	(-1.11)	(-1.12)
2011	1.1779***	-0.0514	-0.0512	-0.0509	1.4525***	-0.0618	-0.0655	-0.0638	0.9432***	-0.0424	-0.0522	-0.0589
	(12.71)	(-1.64)	(-1.55)	(-1.37)	(9.45)	(-1.06)	(-0.87)	(-1.00)	(6.62)	(-0.90)	(-0.84)	(-1.27)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,542	14,542	14,542	14,542	8,179	8,179	8,179	8,179	6,363	6,363	6,363	6,363
Pseudo R^2	0.302	0.302	0.302	0.302	0.240	0.240	0.240	0.240	0.238	0.238	0.238	0.239

*, **, *** Denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
This table presents the marginal effects for a credit ratings model with year indicator variables to examine changes in rating stringency. The dependent variable, *Rating*, is the S&P long-term issuer-level credit rating for firm *i* three months after the end of fiscal year *t*. *LCover*, *LCover_{Neg}*, and *LCover_{WSJ}* are the natural logarithm of 1 plus the number of articles, negative sentiment articles, and articles published in the *Wall Street Journal* written about a firm during the six months ending one year before fiscal year-end, respectively. We report z-statistics below the coefficient estimates based on standard errors clustered by firm.
Variable definitions are presented in Appendix A.

TABLE 4

The Role of Business Press Coverage in the Increasing Stringency of Credit Ratings: Path Analysis

	Rating: Full Sample (1)		*Rating:* Investment Grade (2)		*Rating:* Speculative Grade (3)	
	Coeff.	**Bootstrap z**	**Coeff.**	**Bootstrap z**	**Coeff.**	**Bootstrap z**
Direct Path:						
$Year_t \rightarrow Rating$	0.6437***	4.82	0.4374	1.66*	0.3895	1.87*
Mediated Path:						
I. $Year_t \rightarrow LCover$	8.7488***	19.35	6.2934	15.41***	6.3927	11.27***
II. $LCover \rightarrow Rating$	0.7879***	11.30	0.8939	9.95***	0.4064	5.24***
Indirect Effect (I × II)	6.8935***	8.96	5.6256	7.96***	2.5979	2.96**
Total Effect	7.5372***	16.85	6.0629	13.33***	2.9874	7.54***
Controls	Yes		Yes		Yes	

*, **, *** Denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
This table presents results from the estimation of a structural equation mediation analysis. For purposes of the mediation analysis, we use year indicator variables (omitting 2001) to capture the increase in the stringency of credit ratings relative to 2001. *LCover* is the natural logarithm of 1 plus the number of articles written about a firm during the six months ending one year before fiscal year-end. We include industry fixed effects using three-digit SICs and report z-statistics below the coefficient estimates. We bootstrap all mediation effect statistics.
Variable definitions are presented in Appendix A.

The combined findings in Tables 3 and 4 indicate that business press coverage is an important mediating variable for the increase in ratings stringency since 2001, as documented by Alp (2013) and Baghai et al. (2014). The portion of the increase attributable to the concurrent increase in business press coverage is quite large—being nearly 90 percent for the full sample.

VI. ADDITIONAL ANALYSES

In this section, we provide further tests to reinforce our primary tests and inferences. First, we investigate a mechanism by which the credit rating agencies can affect the quality of ratings for widely covered issuers—the assignment of better educated and more experienced analysts. Second, we investigate whether the credit rating agencies face adverse consequences for missing the prediction of default for widely covered issuers. Third, we examine if higher quality ratings for widely covered issuers vary with regulatory scrutiny and oversight.

Individual Analyst Assignments

In this subsection, we examine if rating agencies strategically allocate analysts to firms with greater business press coverage. Ratings are set and maintained on an ongoing basis through surveillance by a ratings committee; however, individuals with specific knowledge and experience are assigned by managing directors to specific types of issuers (see S&P Global Ratings [2017] for further detail). Accordingly, a potential mechanism through which the credit rating agencies can affect the accuracy and timeliness of more widely covered firms is the assignment of better educated or more experienced analysts. Such analysts should be better at obtaining and understanding credit-relevant information; this can include a greater ability to incorporate public information into their rating assessments (Fracassi et al. 2016). Consistent with the rating agencies strategically assigning analysts, in private conversations, current and former senior-level employees of the major credit rating agencies indicated that a lot of attention is paid to issuers internally. In particular, more senior and experienced analysts, especially those having greater familiarity with the sector and industry, are assigned to issuers with greater visibility and issuers that have complex business or rating analyses. In addition, one employee stated that the more visible the firm is, the bigger the headlines are likely to be and the greater the reputational risk—not only at the rating agency level, but also at the analyst level (i.e., important players in the market tend to know the individual rating analysts).

We formally examine whether the assignment of better analysts is a mechanism through which rating agencies can affect accuracy or timeliness using probit (for dichotomous dependent variables) and OLS (for continuous dependent variables) regressions of nine demographic traits of credit analysts on our business press coverage variable, *LCover,* and our controls for the determinants of business press coverage: *LMktCap, BM, LFollow, InstHold, IVol, Ret, SP500Member, LEmployee, LOwn, NASDAQTraded, Turnover,* and *MomStrength.* We estimate the regressions using issuer-quarter observations, which use average analyst traits for each issuer-quarter. *LCover,* for this analysis, is the natural logarithm of 1 plus the number of articles

written about a firm during the six months ending before the beginning of the quarter. Following Fracassi et al. (2016), we examine the following educational, biological, and employment backgrounds of credit analysts: *MBA, Top 5 MBA, Non-Top 5 MBA, Female Analyst, Analyst Age, Analyst Tenure: Firm, Analyst Tenure: Industry, Analyst Tenure: Agency,* and *# Firms Covered*. We expect that issuers with greater business press coverage will more likely be assigned credit analysts with a Master's of Business Administration (M.B.A.), especially analysts with an M.B.A. from a top five program, that are female and older, with greater experience, and that cover more firms. Regarding the analyst tenure covering firms, greater conflicts of interest can arise when an extended relationship exists between the analyst and the managers of the firm. Accordingly, whether firms with greater business press coverage are assigned analysts for a longer period of time is directionally unclear.

In Table 5, we present findings related to the assignment of higher quality analysts to widely covered firms. Regarding educational background, in column (1), the *LCover* coefficient for *MBA* is statistically positive, indicating that credit analysts with stronger educational backgrounds are increasingly assigned to widely covered firms. In terms of marginal effects (untabulated), an interquartile range increase in *LCover* results in a 7.3 percent increase in the probability of the rating agencies assigning a credit analyst with an M.B.A. In columns (2) and (3), the *LCover* coefficient for *Top 5 MBA* is greater than that for *Non-Top 5 MBA,* providing even further support for analysts of such issuers having stronger educational backgrounds. In columns (4) and (5), the *LCover* coefficients for *Female Analyst* and *Analyst Age* are statistically positive, indicating that female and more experienced analysts are increasingly assigned to widely covered firms.[19] Regarding firm, industry, and agency experience, in columns (6)–(8), we find that the *LCover* coefficients for *Analyst Tenure: Industry* and *Analyst Tenure: Agency* are statistically positive, but fail to find that the *LCover* coefficient for *Analyst Tenure: Firm* is statistically significant. This provides evidence that widely covered firms are more likely to be assigned credit analysts with greater industry and agency tenure, but not those with greater firm tenure, perhaps due to agency problems arising from such relationships. In column (9), the *LCover* coefficient for *# Firms Covered* is significantly positive, lending support to the notion that more experienced analysts are more frequently assigned to more widely covered firms. Regarding the control variables, only a limited number of the determinants of business press coverage explain the assignments of individual credit analysts. Of note, firms with greater turnover, *Turnover,* appear to be assigned better analysts. In sum, the evidence suggests that higher quality analysts are assigned to more widely covered firms, which helps explain how credit rating agencies are able to improve both rating timeliness and accuracy for such firms.

Reputational Consequences of Missed Defaults

Our primary tests assume that the credit rating agencies face greater reputational harm for widely followed issuers when ratings are discovered to be of lower quality. In this subsection, we directly investigate this assumption by testing whether missed defaults, the most prominent attribute of rating quality, lead to more severe consequences for the rating agencies when they involve more widely covered issuers. Our tests investigate four different possibilities: (1) more press coverage discussing rating agencies at missed defaults; (2) lower share of new bond issuances after missed defaults; (3) less reaction to future rating changes; and (4) more negative Moody's stock price response to missed defaults. In addition, we test whether rating agencies respond to missed defaults by improving their performance for existing issuers. These tests include (1) ratings' ability to predict default risk, and (2) changes in rating analyst characteristics for new bond issues.

The results of analyses investigating rating agency consequences for missed defaults are provided in Table 6. The continuous explanatory variables are mean-differenced in all analyses to ease interpretation. In Panel A, we test whether the rating agencies receive more business press coverage at the time of issuer default for widely covered firms, and whether the coverage is more pronounced when a rating agency failed to predict default in the year leading up to the actual default. We test this possibility by regressing $LCover_{Default}$, the natural logarithm of 1 plus the number of articles written about an issuer and rating agency in the two-week window around default for each agency, on *LCover* and E_{TypeI} and the interaction of *LCover* and E_{TypeI}. To focus on stories that discuss a rating agency, we only include stories with a RavenPack reserved relevance score of 20, which identifies designated entities, primarily rating agencies. As presented in Panel A, we find that the coefficients for *LCover* and the interaction of *LCover* and E_{TypeI} are statistically positive. The respective coefficients (i.e., elasticities) of 0.6293 and 0.3293 imply that the sensitivity of default coverage to prior coverage is quite high. This indicates that business coverage of rating agencies of issuer defaults is greater for widely covered issuers, especially when the rating agency had a Type I error leading up to default.

Panel B of Table 6 presents the test of whether credit rating agencies participate in a lower share of new issuances following missed defaults of issuers in the same industry (defined as the Fama-French 12 industries). Our test investigates whether the rating agency is less likely to be employed for a new issuance of a debenture or medium-term note when the agency

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[19] Our finding related to female analysts is consistent with the evidence in Kumar (2010) that only female equity analysts with better forecasting abilities enter a profession that is perceived as discriminatory.

TABLE 5
Additional Analysis: Business Press Coverage and Individual Credit Rating Analyst Characteristics

	MBA (1)	MBA Top 5 (2)	MBA Non-Top 5 (3)	Female Analyst (4)	Analyst Age (5)	Analyst Tenure: Firm (6)	Analyst Tenure: Industry (7)	Analyst Tenure: Agency (8)	# Firms Covered (9)
LCover	0.1563***	0.2463***	0.0099**	0.0288***	0.4156***	−0.0356	0.1544***	0.2620***	0.2342**
	(3.98)	(4.74)	(2.21)	(3.46)	(3.29)	(−1.46)	(5.06)	(3.04)	(2.01)
LSize	0.0021	0.1491	−0.0480	0.0038	0.1066	−0.0859*	0.1457**	0.3775**	1.6338***
	(0.03)	(1.49)	(−0.69)	(0.24)	(0.47)	(−1.79)	(2.20)	(2.52)	(6.34)
BM	−0.0633	−0.1846	−0.0331	0.0220	−0.0866	0.1385*	0.2363***	0.3826*	−0.6241
	(−0.53)	(−1.11)	(−0.30)	(0.84)	(−0.24)	(1.80)	(2.64)	(1.89)	(−1.51)
LFollow	0.0028	0.0028	0.0043	−0.0044***	0.0302	0.0079	0.0116*	0.0242*	0.0478**
	(0.37)	(0.28)	(0.62)	(−2.78)	(1.28)	(1.35)	(1.73)	(1.73)	(2.05)
InstHold	0.4687	−0.0574	0.4509	−0.0426	−0.9848	0.2179	0.1830	−0.0687	2.2913**
	(1.47)	(−0.13)	(1.44)	(−0.62)	(−0.93)	(1.05)	(0.78)	(−0.11)	(2.25)
IVol	−0.2795	−0.0773	−0.3778	−0.0978	−0.6245	−0.5417***	−1.3699***	0.5139	−1.6983
	(−0.93)	(−0.18)	(−1.33)	(−1.34)	(−0.56)	(−2.84)	(−5.39)	(0.92)	(−1.41)
Ret	−0.1374**	0.0640	−0.1292**	−0.0276*	0.1682	−0.1014**	−0.2355***	0.3697***	1.6839***
	(−2.05)	(0.55)	(−1.99)	(−1.82)	(0.67)	(−2.01)	(−3.69)	(3.06)	(6.45)
SP500	−0.0338	−0.2296	−0.0017	0.0064	0.3291	0.0787	0.0684	0.3196	−1.5086**
	(−0.17)	(−0.98)	(−0.01)	(0.15)	(0.54)	(0.64)	(0.45)	(0.89)	(−2.40)
LEmployee	−0.1045	−0.3121***	0.0011	0.0849***	0.6015***	0.0547	0.0045	0.5909***	1.0896***
	(−1.63)	(−3.36)	(0.02)	(5.87)	(3.17)	(1.51)	(0.10)	(4.89)	(5.75)
LOwn	−0.0096	0.0706	−0.0324	0.0016	−0.0724	0.0312	−0.0186	−0.1769*	−0.2976*
	(−0.20)	(0.99)	(−0.74)	(0.14)	(−0.48)	(1.02)	(−0.51)	(−1.79)	(−1.87)
NASDAQ	0.0601	−0.7977***	0.1798	0.0887**	0.2759	−0.1716	−0.0662	0.2669	−0.2297
	(0.36)	(−2.88)	(1.11)	(2.50)	(0.47)	(−1.61)	(−0.51)	(0.85)	(−0.40)
Turnover	11.5395	28.8905**	8.6669	−1.6593	99.0626***	36.6600***	67.5562***	27.6738	2.8123
	(1.39)	(2.37)	(1.08)	(−0.82)	(3.24)	(4.91)	(9.12)	(1.56)	(0.10)
MomStrength	0.1019	0.0783	0.0720	0.0527**	−0.0358	0.1185	0.0571	−0.3128	−0.0116
	(0.71)	(0.45)	(0.58)	(2.12)	(−0.09)	(1.23)	(0.50)	(−1.40)	(−0.02)
Constant	1.0083	−3.2429***	0.9587*		38.2047***	0.7704**	1.8738***	2.3197**	23.9390***
	(1.64)	(−4.09)	(1.69)		(21.00)	(2.19)	(3.84)	(2.09)	(12.36)
Observations	20,573	20,573	20,573	20,573	20,510	20,573	20,573	18,118	20,573
Pseudo/Adjusted R²	0.032	0.037	0.006	0.036	0.028	0.074	0.094	0.074	0.067

*, **, *** Denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

This table presents the results of estimating probit (columns (1)–(4)) and OLS regressions (columns (5)–(9)) to investigate the role of business press coverage on the assignment of credit analysts with certain characteristics. Standard errors are clustered two-way by firm and quarter. The dependent variables capture different credit rating analyst traits and include:

MBA = an indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree, and 0 otherwise;

Top 5 MBA = an indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree from a top five program, and 0 otherwise (top five M.B.A. programs are from the 2011 *Economist* ranking and include The University of Chicago, Tuck School of Business, the Haas School of Business at University of California, Berkeley, University of Virginia, and IESE Business School);

TABLE 5 (continued)

Non-Top 5 MBA = an indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree from a non-top five program, and 0 otherwise;

Female Analyst = an indicator variable set equal to 1 if the credit rating analyst's gender is female, and 0 otherwise;

Analyst Age = the minimum of the first year of employment minus 22 years, and the first year of college minus 18 years;

Analyst Tenure: Firm = the number of years between the date an analyst covers a firm for the first time and the date on which the quarter ends;

Analyst Tenure: Industry = the number of years between the date an analyst covers a company in the industry in which the rated firm operates for the first time (Fama-French 49 classification) and the date on which the quarter ends;

Analyst Tenure: Agency = the number of years between the date an analyst starts working for the rating agency and the date on which the quarter ends;

 # Firms Covered = the number of firms covered by the credit rating analyst at the end of the quarter; and

LCover = the natural logarithm of 1 plus the number of articles written about a firm during the six months ending before the beginning of the quarter.

Variable definitions are presented in Appendix A.

TABLE 6

Additional Analysis: Reputational Consequences of Missed Defaults

Panel A: Business Press Coverage Mentioning Rating Agency at Issuer Defaults

	$LCover_{Default}$ (1)
$LCover$	0.6293***
	(22.40)
E_{TypeI}	0.1299***
	(4.62)
$LCover \times E_{TypeI}$	0.3293***
	(10.04)
Constant	0.2966***
	(13.69)
Observations	531
Adjusted R^2	0.876

Panel B: Demand for Credit Ratings following Missed Defaults

	$Hired$ (1)
$LCover_{Industry,t-1}$	0.0422
	(1.57)
$E_{TypeI,Industry,t-1}$	−1.8871***
	(−6.78)
$LCover_{Industry,t-1} \times E_{TypeI,Industry,t-1}$	−0.2985***
	(−4.52)
Constant	−0.1698
	(−0.92)
Observations	207,849
Pseudo R^2	0.337

TABLE 6 (continued)

Panel C: Stock Market Response to Rating Changes following Missed Defaults

	$CAR_{0,+1}$	
	(1) Downgrades	(2) Upgrades
$LCover_{Industry,t-1}$	0.0016	0.0006
	(0.71)	(0.86)
$E_{TypeI,Industry,t-1}$	0.0149***	−0.0054**
	(3.88)	(−2.28)
$LCover_{Industry,t-1} \times E_{TypeI,Industry,t-1}$	0.0102***	−0.0008*
	(2.87)	(−1.75)
Constant	−0.0564***	0.0141**
	(−3.68)	(2.15)
Observations	67,369	30,220
Adjusted R^2	0.038	0.013

Panel D: Moody's Stock Price Reaction to Issuer Defaults

	$CARMoody's_{0,+1}$
	(1)
$LCover$	0.0025**
	(2.29)
E_{TypeI}	−0.0261**
	(−2.42)
$LCover \times E_{TypeI}$	−0.0057***
	(−3.21)
Constant	0.0122*
	(1.73)
Observations	1,102
Adjusted R^2	0.126

TABLE 6 (continued)

Panel E: Rating Agencies' Default Risk Prediction following Missed Defaults

	EDF_{t+1} (1)	EDF_{t+3} (2)	EDF_{t+5} (3)
Rating	0.0073*** (11.63)	0.0032*** (4.00)	0.0034*** (4.90)
Rating $\times$ $E_{TypeI,Industry,t-1}$	0.0051*** (6.78)	0.0033*** (4.12)	0.0025*** (3.14)
Rating $\times$ $E_{TypeI,Industry,t-1}$ $\times$ $LCover_{Industry,t-1}$	0.0008*** (9.72)	0.0003** (2.15)	0.0007*** (4.27)
Rating $\times$ $E_{TypeI,Industry,t-1}$ $\times$ $LCover$	0.0006*** (4.98)	0.0006*** (3.28)	0.0004** (2.16)
$E_{TypeI,Industry,t-1}$	−0.0316*** (−5.15)	−0.0179*** (−2.59)	0.0049 (0.76)
$LCover_{Industry,t-1}$	0.0076*** (5.41)	−0.0067*** (−5.36)	0.0059*** (3.18)
$LCover$	0.0055** (2.21)	0.0013 (0.48)	−0.0038 (−1.13)
Rating $\times$ $LCover_{Industry,t-1}$	0.0012*** (8.16)	0.0006*** (3.59)	0.0001 (0.41)
Rating $\times$ $LCover$	0.0009*** (3.11)	0.0008*** (2.85)	0.0010*** (2.61)
Constant	−0.0380*** (−6.63)	0.0079 (1.00)	−0.0056 (−0.86)
Observations	15,170	11,481	8,191
Adjusted R²	0.051	0.032	0.027

Panel F: Analyst Characteristics for New Bond Issues following Missed Defaults

	MBA (1)	Top 5 MBA (2)	Non-Top 5 MBA (3)	Female Analyst (4)	Analyst Age (5)	Analyst Tenure: Firm (6)	Analyst Tenure: Industry (7)	Analyst Tenure: Agency (8)	# Firms Covered (9)
$LCover$	0.1650*** (3.71)	0.2220*** (4.05)	0.0051** (2.09)	0.1719*** (4.27)	0.4854*** (3.61)	−0.0527* (−1.82)	0.2482*** (6.89)	0.3364*** (3.42)	0.6359*** (5.56)
$E_{TypeI,Industry,t-1}$ $\times$ $LCover_{Industry,t-1}$	0.1007** (2.41)	0.1636** (2.44)	0.0350 (0.87)	0.1591*** (4.29)	0.4319*** (2.93)	−0.0438 (−1.30)	0.0871** (2.10)	0.1236 (1.30)	0.2358* (1.79)
$E_{TypeI,Industry,t-1}$ $\times$ $LCover$	0.1148*** (2.81)	0.3779*** (5.36)	0.0741* (1.95)	0.1277*** (3.51)	0.1745 (1.16)	−0.0143 (−0.46)	0.0890** (2.32)	0.1896** (2.04)	0.2845** (2.07)
$E_{TypeI,Industry,t-1}$	0.3368*** (2.66)	0.8495*** (3.13)	0.2167* (1.80)	0.2700** (2.53)	1.0000** (2.10)	−0.1551* (−1.90)	0.3830*** (3.50)	0.4744* (1.78)	4.5627*** (9.55)

TABLE 6 (continued)

	MBA (1)	Top 5 MBA (2)	Non-Top 5 MBA (3)	Female Analyst (4)	Analyst Age (5)	Analyst Tenure: Firm (6)	Analyst Tenure: Industry (7)	Analyst Tenure: Agency (8)	# Firms Covered (9)
$LCover_{Industry,t-1}$	−0.0071	0.0274	−0.0478	0.1059***	−0.2686*	0.0820***	0.0965**	0.0090	−0.3593***
	(−0.19)	(0.52)	(−1.39)	(3.28)	(−1.94)	(2.61)	(2.53)	(0.10)	(−3.55)
Constant and *LCover* Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,461	9,461	9,461	9,461	9,461	9,461	9,461	7,108	9,461
Pseudo/Adjusted R²	0.039	0.051	0.006	0.040	0.031	0.077	0.098	0.078	0.088

*, **, *** Denote two-sided statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Continuous explanatory variables are mean-differenced to ease interpretation. This table reports the results of estimating models of the consequences of missed defaults for rating agencies. Panel A reports default coverage that includes reference to a rating agency. The dependent variable, $LCover_{Default}$, is the natural logarithm of 1 plus the number of articles written about a firm and a rating agency in the two-week window around each default event and agency. Panel B reports the relation between missed defaults and subsequent rating engagements for new bond issues. The dependent variable, *Hired*, is an indicator variable set equal to 1 when the credit rating agency is hired to provide a rating on the new issuance, and 0 otherwise. Panel C reports the stock market response to credit rating upgrades and downgrades of continuing issuers following defaults of rating agencies' client issuers. The dependent variable, $CAR_{0,+1}$, is the two-day stock return for a downgrade or upgrade announcement. Panel D reports the stock price response of Moody's Investors Service around the defaults of its client firms. The dependent variable, $CARMoody's_{0,+1}$, is the two-day stock return for Moody's at a firm's default announcement. Panel E reports the ability of ratings to predict future expected default frequencies following defaults of rating agencies' client issuers. The dependent variable, EDF_{t+j}, is expected default frequency for $j = 1, 3, 5$ years following default at time t. Panel F reports changes in bond rating agency analyst characteristics for newly issued bonds following defaults of rating agencies' client issuers. The dependent variables capture different credit rating analyst traits and include:

MBA = an indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree, and 0 otherwise;

$Top 5 MBA$ = an indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree from a top five program, and 0 otherwise (top five M.B.A. programs are from the 2011 *Economist* ranking and include The University of Chicago, Tuck School of Business, the Haas School of Business at University of California, Berkeley, University of Virginia, and IESE Business School);

$Non-Top 5 MBA$ = an indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree from a non-top five program, and 0 otherwise;

$Female Analyst$ = an indicator variable set equal to 1 if the credit rating analyst's gender is female, and 0 otherwise;

$Analyst Age$ = the minimum of the first year of employment minus 22 years, and the first year of college minus 18 years;

$Analyst Tenure: Firm$ = the number of years between the date an analyst covers a firm for the first time and the date on which the quarter ends;

$Analyst Tenure: Industry$ = the number of years between the date an analyst covers a company in the industry in which the rated firm operates for the first time (Fama-French 49 classification) and the date on which the quarter ends;

$Analyst Tenure: Agency$ = the number of years between the date an analyst starts working for the rating agency and the date on which the quarter ends; and

$\# Firms Covered$ = the number of firms covered by the credit rating analyst at the end of the quarter.

t-/z-statistics are reported below coefficient estimates and are calculated using robust standard errors clustered two-way by firm and year. The variables of interest and their interactions are:

$LCover$ = the natural logarithm of 1 plus the number of articles written about a firm during the six months ending one year before a default date or fiscal year-end;

E_{TypeI} = an indicator variable set equal to 1 if a bond possesses a credit rating of B−/B3 or less favorable one year before a default event, and 0 otherwise;

$LCover_{Industry,t-1}$ = the natural logarithm of 1 plus the number of articles written about a defaulting firm (or average number of articles about multiple defaulting firms) during the six months ending one year prior to default date; and

$E_{TypeIIndustry,t-1}$ = an indicator variable set equal to 1 when the credit rating agency had a Type I error in the same industry as the issuer during the last year, and 0 otherwise. Variable definitions are presented in Appendix A.

had a Type I error in the prior year in the same industry as the issuer, and whether the lower likelihood is more pronounced when the defaulting issuer had greater business press coverage. The dependent variable for this analysis, *Hired,* is an indicator variable set equal to 1 when the credit rating agency is hired to provide a rating on the new issuance, and 0 otherwise. The explanatory variables are $E_{TypeI,Industry,t-1}$, an indicator variable set equal to 1 when the credit rating agency had a Type I error in the same industry as the issuer during the last year, and 0 otherwise; $LCover_{Industry,t-1}$, the natural logarithm of 1 plus the number of articles written about a defaulting firm (or average number of articles about multiple defaulting firms) during the six months ending one year prior to a default date; and the interaction between $E_{TypeI,Industry,t-1}$ and $LCover_{Industry,t-1}$. Consistent with credit rating agencies losing business following missed defaults, especially when the missed defaults relate to high-visibility issuers, we find that the coefficients for $E_{TypeI,Industry,t-1}$ and the interaction between $E_{TypeI,Industry,t-1}$ and $LCover_{Industry,t-1}$ are significantly negative. In terms of magnitude, on average, committing a Type I error reduces the likelihood of a rating agency being hired by 40 percentage points. In addition, the marginal effect of committing a Type I error on a rating agency being hired in the future increases in magnitude by nearly 24 percentage points for an interquartile range increase in $LCover_{TypeI,Industry,t-1}$.

In our third test, presented in Panel C of Table 6, we examine whether the stock market reaction to rating downgrades and upgrades differs when a credit rating agency has missed a default in the industry, conditioning on the coverage of the issuer. This test involves regressing the rating downgrade or upgrade announcement period return, $CAR_{0,+1}$, on whether there was a Type I error in the prior year in the same industry as the issuer, $E_{TypeI,Industry,t-1}$; on the business press coverage of the defaulting issuer (or average coverage if multiple defaulting issuers), $LCover_{Industry,t-1}$; and the interaction between the two variables, $E_{TypeI,Industry,t-1} \times LCover_{Industry,t-1}$. If rating changes by a rating agency are given less weight following a missed default by the agency in the same industry over the prior year, then we expect that the coefficient for $E_{TypeI,Industry,t-1}$ will be positive and negative for downgrades and upgrades, respectively. If the market places less weight on ratings changes when the missed default has greater visibility, then we expect that the coefficient for the interaction between $E_{TypeI,Industry,t-1}$ and $LCover_{Industry,t-1}$ will be positive and negative for downgrades and upgrades, respectively. In Panel C, we find evidence consistent with these predictions. The mitigation in the market reaction is fairly large for downgrades and moderate for upgrades. For downgrades and upgrades, the coefficients for $E_{TypeI,Industry,t-1}$ are 0.0149 and -0.0054, and the coefficients for the interaction between $E_{TypeI,Industry,t-1}$ and $LCover_{Industry,t-1}$ are 0.0102 and -0.0008, respectively. This indicates that credit rating revisions provide private information to investors, but that market participants place less weight on ratings after observing that rating quality is lower and when lower quality is more visible to market participants.

In the last test of reputational consequences of missed defaults for rating agencies, presented in Table 6, Panel D, we directly investigate whether rating agencies suffer economic losses by examining the market reaction of Moody's stock price to announcements of missed defaults.[20] We regress Moody's two-day return, $CARMoody's_{,0,+1}$, for each default announcement on $LCover$ and E_{TypeI} and the interaction of $LCover$ and E_{TypeI}. We expect that stock returns will be more negative when Moody's fails to warn of a default in advance (i.e., when $E_{TypeI} = 1$) and that the reaction will be even more negative for widely covered issuers, consistent with the failure being more visible to market participants. As shown in the panel, we find that the coefficients for E_{TypeI} and the interaction of $LCover$ and E_{TypeI} are statistically negative. The coefficients are fairly large at -0.0261 and -0.0057, respectively. This evidence suggests that Moody's incurs reputational costs from not providing early warnings of defaults of issuers, especially when the issuers are highly visible.

Taken together, this evidence supports our assumption that the rating agencies face reputational harm for low-quality ratings, and that the harm is more severe for more visible issuers. These costs, ranging from negative visibility to reduced credibility and lower future revenues, could ultimately lower firm value.

Our final two tests related to the reputational consequences of missed defaults investigate how the rating agencies respond to missed defaults. If rating agencies bear some reputational harm from missed defaults, then they should attempt to rebuild the reputational damage with their remaining clients. We test two possible ways in which rating agencies themselves can respond: (1) improving the accuracy of their ratings of outstanding (non-defaulting) issues, and (2) improving the quality of the rating analysts assigned to new rating engagements in an effort to minimize the risk of further rating failures. To test whether rating agencies improve their accuracy following missed defaults, similar to Kedia, Rajgopal, and Zhou (2014) and Bonsall, Koharki, and Neamtiu (2017), we examine how ratings' ability to predict future default risk after missed defaults changes using expected default frequencies (EDFs). We report our results from this test in Panel E of Table 6. Consistent with prior research, we find a positive association between credit ratings and future EDFs for periods ranging from one to five years into the future. Next, we document positive estimated coefficients on $Rating \times E_{TypeI,Industry,t-1}$, which are suggestive of improvements in rating accuracy following missed defaults. Furthermore, we find that the improvement in rating accuracy following missed defaults is

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[20] We investigate only Moody's stock price reaction because of it being an NYSE-listed company. Standard & Poor's and Fitch are privately held and private, respectively.

greater when the business press coverage of the defaulted firms is greater ($Rating \times E_{TypeI,Industry,t-1} \times LCover_{Industry,t-1} > 0$) and when business press coverage of a surviving (non-defaulting) firm is greater ($Rating \times E_{TypeI,Industry,t-1} \times LCover > 0$). Thus, it appears that rating agencies respond to missed defaults by improving the accuracy of their ratings for the non-defaulting clients.

While the evidence in Panel E of Table 6 points toward improvements in the accuracy of ratings following missed defaults, it is unclear why this seems to occur. We test whether the attributes of rating analysts, as explored in Table 5, assigned to new bond issues change following missed defaults in ways that are consistent with the evidence of improved rating quality shown in Panel E of Table 6. We report our findings with respect to changes in analyst characteristics in Panel F of Table 6. We find broad evidence that rating agencies assign better analysts onto new rating engagements in the year following a missed default in the same industry. Furthermore, we find reasonably consistent evidence that the assignment of higher quality analysts after missed defaults is more pronounced when there is greater business press coverage of the defaulting firm for which the rating was too optimistic ($E_{TypeI,Industry,t-1} \times LCover_{Industry,t-1}$) and when there is greater coverage of the non-defaulting firm issuing the new bond ($E_{TypeI,Industry,t-1} \times LCover$). Overall, it appears that rating agencies respond to missed defaults by assigning higher quality analysts to new bond issues in industries where the rating failures occurred, particularly when the missed default was related to a more visible issuer and when a new bond is issued by a more visible firm. These results help explain our evidence that rating accuracy improves following missed defaults—potentially as a way to rebuild the lost reputational capital from missed defaults.

Rating Properties Following the Financial Crisis

The credit rating agencies faced considerable reputational harm following their failure to properly assess the default risk of structured finance products before the financial crisis. Their perceived lack of care ultimately led to increased regulatory scrutiny and oversight, including the passage of the Dodd-Frank Act. As demonstrated by Mathis et al. (2009), credit rating agencies can engage in "inefficient credit cycles," where the rating agencies can profit from their reputations by reducing the quality of their ratings during booms and then rebuilding their reputations after prominent rating failures. Consistent with spillover from the ratings failure for structured finance products affecting corporate ratings, Dimitrov et al. (2015) and deHaan (2017) provide evidence that the rating agencies improved the quality of their corporate credit ratings following the financial crisis. For instance, in the post-crisis period, deHaan (2017) finds that the credit rating agencies have lower Type I and Type II errors, lower rating volatility, and more timely ratings.

We investigate whether the shift in regulatory scrutiny and oversight led to business press coverage being more important following the financial crisis, due to the higher costs of rating failures for high-profile issuers. That is, because regulators are more likely to become aware of rating failures related to high-profile issuers, they are most likely to take actions for rating failures by such issuers. Improvements in the properties of ratings could also come from investors and issuers being more aware of or sensitive to the quality of corporate ratings following the financial crisis, especially for more prominent and visible issuers. Together, this leads to the prediction that the shift in the quality of ratings following the financial crisis is more likely to affect high-visibility issuers. To test this possibility, we reestimate our primary models with an interaction between *LCover* and *PostCrisis,* an indicator variable set equal to 1 for periods after July 1, 2009, and 0 otherwise, similar to deHaan (2017).

Table 7 presents the findings for the post-crisis analysis. For the sake of parsimony, we suppress the results for the control variables. In Panel A, in our analysis of *Days* and $\overline{Rating}$, we find that the coefficients for *LCover* are significantly negative and positive, respectively, and the coefficients for the interaction between *LCover* and *PostCrisis* are significantly negative and positive, respectively. Combined, this evidence indicates that more widely covered issuers have more timely ratings and that the timeliness increased following the financial crisis. In Panel B, in our analysis of E_{TypeI} and E_{TypeII}, we find that the coefficients for *LCover* and the interaction between *LCover* and *PostCrisis* are significantly negative. This evidence indicates that more widely covered issuers have more accurate ratings and that the accuracy increased following the financial crisis. In Panel C, in our rating stringency analysis using *Rating,* we find that the coefficients for *LCover* and the interaction between *LCover* and *PostCrisis* are significantly positive. This evidence indicates that the more stringent ratings for widely covered issuers grew even more stringent following the financial crisis, and demonstrates that our earlier results for *LCover* are not driven by the concurrent shift in regulatory regime. Overall, we find that increased regulatory attention following the financial crisis is not uniform across issuers, but is concentrated in those most likely to receive regulatory attention—i.e. high-visibility issuers.

VII. SUMMARY AND CONCLUSION

Because of the oligopoly enjoyed by the major credit rating agencies, various parties have raised concerns that the rating agencies do not face the same market-based disciplining forces as do other institutions in competitive markets, such as the

TABLE 7

Additional Analysis: Moderating Effects of the 2007–2009 Financial Crisis

Panel A: Default Rating Timeliness

	Days (1)	$\overline{Rating}$ (2)
LCover	−23.1202***	0.3400***
	(−5.87)	(3.37)
PostCrisis	−1.9834**	5.4628***
	(−1.98)	(4.72)
LCover × PostCrisis	−7.1458***	0.6478***
	(−3.52)	(2.83)
Constant	118.6886	0.1490
	(0.81)	(0.05)
Rating Timeliness Controls	Yes	Yes
Coverage Controls	Yes	Yes
Observations	9,888	3,754
Adjusted R^2	0.532	0.917

Panel B: Rating Accuracy

	E_{TypeI} (1)	E_{TypeII} (2)
LCover	−0.2138***	−0.0931***
	(−4.30)	(−3.90)
PostCrisis	−1.5283**	−0.0079
	(−2.43)	(−0.06)
LCover × PostCrisis	−0.1029***	−0.0751***
	(−5.91)	(−2.92)
Constant	−5.5137***	−2.2487***
	(−2.75)	(−4.85)
Rating Accuracy Controls	Yes	Yes
Coverage Controls	Yes	Yes
Observations	3,461	484,482
Pseudo R^2	0.601	0.368

incentive to develop and sustain performance-based reputations. We investigate a possible meaningful mechanism—coverage by the business press—that leads the major credit rating agencies to be more effective monitors of issuers' creditworthiness. Our prediction that the rating agencies will be more effective monitors of widely followed issuers is based on the idea that low-quality ratings of such issuers are more prominent to outsiders (e.g., investors, regulators, and the public), and that the business press itself is likely to be more critical of the low-quality ratings of widely covered firms, which can lead to higher reputational costs for rating agencies.

Using a large sample of debt issuers and an extensive set of news stories from RavenPack, we find that more widely covered issuers have more timely ratings, providing earlier warnings of actual defaults. Further, we find that more widely covered issuers have more accurate ratings—predicting defaults correctly (i.e., Type I errors) and not providing false warnings of default (i.e., Type II errors). We also find that the evidence that corporate credit rating standards have become more stringent over time is, in large part, explained by the concurrent increase in coverage by the business press—i.e., greater business press coverage of issuers has resulted in more stringent ratings. In addition, these improvements appear to occur through the credit rating agencies assigning better educated and more experienced analysts to widely covered issuers. Finally, high-visibility issuers create greater reputational consequences (e.g., lost future ratings of new issuances) following rating agencies' failure to predict default, and have greater improvements in rating performance following the regulatory attention brought about by the financial crisis.

TABLE 7 (continued)

Panel C: Rating Stringency

	Rating (1)
LCover	1.2729***
	(7.45)
LCover × PostCrisis	0.0836***
	(2.99)
Year:	
2002	−0.0489
	(−0.73)
2003	0.0100
	(0.16)
2004	−0.0776
	(−0.85)
2005	0.0553
	(0.61)
2006	0.1599*
	(1.69)
2007	0.1404
	(1.28)
2008	0.1953
	(1.55)
2009	0.0654
	(1.03)
2010	−0.0902*
	(−1.75)
2011	−0.0335
	(−0.89)
Rating Controls	Yes
Coverage Controls	Yes
Industry Fixed Effects	Yes
Observations	14,542
Adjusted R^2	0.302

*, **, *** Denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
This table presents the results of estimating regressions that interact an indicator variable for observations after June 2009 (*PostCrisis*) with *LCover* for each of our primary analyses. Panel A presents default rating timeliness regressions. The dependent variable in column (1) is *Days:* the number of days between the downgrade of the bond to BB/Ba or lower (i.e., the downgrade is to speculative grade) and the default date (maximum value of 0, minimum value of −360); and in column (2) is $\overline{Rating}$: the average credit rating over the year prior to the default date (weighted by the number of days each rating was outstanding). Panel B presents rating accuracy regressions. The dependent variable in column (1) is E_{TypeI}, an indicator variable set equal to 1 if a bond possesses a credit rating of B−/B3 or less favorable one year before a default event, and 0 otherwise, and in column (2) is E_{TypeII}, an indicator variable set equal to 1 if a bond possesses a credit rating of CCC+/Caa1 or less favorable one year before a non-default event, and 0 otherwise. Panel C presents a rating stringency regression. The dependent variable is *Rating:* the S&P long-term issuer-level credit rating for firm *i* three months after the end of fiscal year *t*. As in the primary analyses, the primary variable of interest is *LCover,* the natural logarithm of 1 plus the number of articles written about a firm during the six months ending one year before a default date, a non-default date, or a fiscal year-end. Standard errors are clustered two-way by firm and quarter or year depending on the specification.
Variable definitions are presented in Appendix A.

These findings provide insight into how the business press can influence the monitoring activities of other market participants—in this case, creating a complementary relationship with the major credit rating agencies. In addition, these findings provide insight into the recent tightening of rating standards over time documented by prior research.

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APPENDIX A

Dependent Variables, Variables of Interest, and Control Variables

Panel A: Dependent Variables

Variable		Description
Days	=	the number of days between the downgrade of the bond to BB/Ba or lower (i.e., the downgrade is to speculative grade) and the default date (maximum value of 0, minimum value of −360).
$\overline{Rating}$	=	the average credit rating over the year prior to the default date (weighted by the number of days each rating was outstanding). Ratings are coded higher when closer to default (i.e., AAA/Aaa = 1, C/C = 21).
E_{TypeI}	=	indicator variable set equal to 1 if a bond possesses a credit rating of B−/B3 or more favorable one year before a default event, and 0 otherwise.
E_{TypeII}	=	indicator variable is set equal to 1 if a bond possesses a credit rating of CCC+/Caa1 or less favorable one year before a non-default event, and 0 otherwise.
Rating	=	S&P long-term issuer-level credit rating for firm *i* three months after the end of fiscal year *t*.
MBA	=	indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree, and 0 otherwise.
Top 5 MBA	=	indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree from a top five program, and 0 otherwise (top five M.B.A. programs are from the 2011 *Economist* ranking and include The University of Chicago, Tuck School of Business, the Haas School of Business at University of California, Berkeley, University of Virginia, and IESE Business School).
Non-Top 5 MBA	=	indicator variable set equal to 1 if the credit rating analyst has a Master's of Business Administration (M.B.A.) degree from a non-top five program, and 0 otherwise.
Female Analyst	=	indicator variable set equal to 1 if the credit rating analyst's gender is female, and 0 otherwise.
Analyst Age	=	minimum of the first year of employment minus 22 years, and the first year of college minus 18 years.
Analyst Tenure : Firm	=	the number of years between the date an analyst covers a firm for the first time and the date on which the quarter ends.
Analyst Tenure: Industry	=	the number of years between the date an analyst covers a company in the industry in which the rated firm operates for the first time (Fama-French 49 classification) and the date on which the quarter ends.
Analyst Tenure: Agency	=	the number of years between the date an analyst starts working for the rating agency and the date on which the quarter ends.
# Firms Covered	=	the number of firms covered by the credit rating analyst at the end of the quarter.

(continued on next page)

APPENDIX A (continued)

Variable		Description
LCoverDefault	=	natural logarithm of 1 plus the number of articles written about a firm and a rating agency in the two-week window around each default event and agency.
Hired	=	indicator variable set equal to 1 when the credit rating agency is hired to provide a rating on the new issuance, and 0 otherwise;
$CAR_{0,+1}$	=	the two-day stock return for a downgrade or upgrade announcement.
$CARMoody's_{0,+1}$	=	the two-day stock return for Moody's at a firm's default announcement.
EDF_{t+j}	=	expected default frequency for $j = 1, 3, 5$ years following default at time t.

Panel B: Business Press Coverage Variables and Other Variables of Interest

Variable		Description
LCover	=	natural logarithm of 1 plus the number of articles written about a firm during the six months ending one year before a default date, non-default date, or fiscal year-end.
$LCover_{Neg}$	=	natural logarithm of 1 plus the number of negative sentiment articles written about a firm during the six months ending one year before a default date, non-default date, or fiscal year-end.
$LCover_{WSJ}$	=	natural logarithm of 1 plus the number of articles written about a firm in the *Wall Street Journal* during the six months ending one year before a default date, non-default date, or fiscal year-end.
$LCover_{Industry,t-1}$	=	natural logarithm of 1 plus the number of articles written about a defaulting firm (or average number of articles about multiple defaulting firms) during the six months ending one year prior to a default date.
$E_{TypeI,Industry,t-1}$	=	indicator variable set equal to 1 when the credit rating agency had a Type I error in the same industry as the issuer during the last year, and 0 otherwise.
PostCrisis	=	an indicator variable set equal to 1 for periods after July 1, 2009, and 0 otherwise.
%PRNotBusy	=	the percentage of an issuer firm's press releases (over the same fiscal year window used to measure *LCover*) issued on days when the number of press releases made by firms outside the issuer firm's three-digit SIC is below the average for the year.
%PRWSJBusy	=	the percentage of an issuer firm's press releases (over the same fiscal year window used to measure *LCover*) issued on days when the percentage of non-business news in the *Wall Street Journal* is in the top quartile for the year.

Panel C: Determinants of Coverage Controls

Variable		Description
LMktCap	=	natural logarithm of market value of equity.
BM	=	book value of stockholders' equity divided by market capitalization.
LFollow	=	natural logarithm of 1 plus the number of equity analysts following the firm during the most recent fiscal year.
InstHold	=	percentage of shares held by institutional investors.
IVol	=	annualized standard deviation of weekly residual returns based on the following model from Bandarchuk and Hilscher (2013): $r_{it} = a_i + b_i r_{mt} + \gamma_i r_{It} + e_{it}$.
Ret	=	buy-and-hold return during the previous 12 months.
SP500Member	=	indicator variable set equal to 1 if a firm is a member of the S&P 500 market index, and 0 otherwise.
LEmployee	=	natural logarithm of the number of employees.
LOwn	=	natural logarithm of the number of shareholders.
NASDAQTraded	=	indicator variable set equal to 1 if a firm's common shares trade on the NASDAQ, and 0 otherwise.
Turnover	=	average share volume divided by shares outstanding using daily stock market data over the last six months.
MomStrength	=	absolute value of the difference between the firm's stock return over the previous six months and the median stock return over the same period (Bandarchuk and Hilscher 2013).

Panel D: Other Controls (in order of appearance)

Variable		Description
SPRating	=	indicator variable equal to 1 if a rating is from S&P, and 0 otherwise.
FitchRating	=	indicator variable equal to 1 if a rating is from Fitch, and 0 otherwise.
Bankruptcy	=	indicator variable equal to 1 if a default is related to an issuer's bankruptcy filing, and 0 otherwise.
LAsset	=	natural logarithm of an issuer's total assets at the end of the most recent quarter prior to one year before the default date.

American Accounting Association

APPENDIX A (continued)

Variable		Description
IntCover	=	ratio of an issuer's income before extraordinary items to interest expense during the most recent quarter prior to one year before the default date.
DebtEquity	=	issuer's ratio of total debt to stockholders' equity at the end of the most recent quarter prior to one year before the default date.
LFace	=	natural logarithm of the bond's issue amount in $millions.
AssetBacked	=	indicator variable equal to 1 if a bond is an asset-backed issue, and 0 otherwise.
Convertible	=	indicator variable equal to 1 if a bond has a conversion feature, and 0 otherwise.
Senior	=	indicator variable equal to 1 if a bond possesses senior status, and 0 otherwise.
Enhance	=	indicator variable equal to 1 if a bond possesses credit enhancements, and 0 otherwise.
Put	=	indicator variable equal to 1 if a bond is putable, and 0 otherwise.
Redeem	=	indicator variable equal to 1 if a bond is redeemable, and 0 otherwise.
Maturity	=	number of years until a bond's maturity.
Rating	=	credit rating of the bond one year before the default date.
GDP	=	gross domestic product for the United States during the year leading up to one year before the default date.
CRSPBond	=	12-month return on the 30-year Treasury bond prior to one year before the default date.
SP500	=	value of the S&P 500 index one year before the default date.
LDefaults	=	number of defaults occurring during the most recent quarter prior to one year before the default date.
LargeLoss	=	indicator variable equal to 1 if an issuer experiences an annual loss greater than or equal to 25 percent of total assets during the fiscal year ending prior to one year before the default date, and 0 otherwise.
NegRetain	=	indicator variable equal to 1 if an issuer reports negative retained earnings at the end of the fiscal year prior to one year before the default date, and 0 otherwise.
IntCov	=	EBITDA divided by interest expense.
Profit	=	EBITDA divided by sales.
Book_Lev	=	long- and short-term debt divided by total assets.
Debt/EBITDA	=	long- and short-term debt divided by EBITDA.
Neg.Debt/EBITDA	=	indicator variable set equal to 1 if *Debt/EBITDA* is negative, and 0 otherwise.
Vol	=	volatility of profitability, computed using the current year's data, as well as the four previous years' (with at least two years of data required).
Cash/Assets	=	cash and marketable securities divided by total assets.
ConvDe/Assets	=	convertible debt divided by total assets.
Rent/Assets	=	rental payments divided by total assets.
PPE/Assets	=	net property, plant, and equipment divided by total assets.
CAPEX/Assets	=	capital expenditures divided by total assets.
Beta	=	stock's Dimson-adjusted beta (one lead and one lag term) computed with daily returns (standardized by dividing them by their annual cross-sectional means).
Idio.Risk	=	root mean squared error from a regression of daily stock returns on CRSP value-weighted index returns (standardized by dividing them by their annual cross-sectional means).

APPENDIX B

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