THE ACCOUNTING REVIEW
Vol. 98, No. 7
November 2023
pp. 347–376

American Accounting Association
DOI: 10.2308/TAR-2021-0874

The Usefulness of Credit Ratings for Accounting Fraud Prediction

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ABSTRACT: This study examines whether and when credit ratings are useful for accounting fraud prediction. We find that negative rating actions by Standard & Poor's (S&P), an issuer-paid credit rating agency (CRA), have predictive ability for fraud incremental to fraud prediction models (e.g., *F-score*) and other market participants. In contrast, rating actions by Egan-Jones Rating Company (EJR), an investor-paid CRA relying on public information, have less predictive ability, which is subsumed by S&P and other market participants. Our results are robust to including firms not covered by EJR, using only rating downgrades, controlling for firm characteristics, and using alternative benchmarks. We also find that the ability of negative S&P rating actions to predict fraud becomes stronger after the 2008–2009 financial crisis. Last, compared with EJR, S&P is quicker to take negative rating actions against fraud firms. In sum, our results suggest that issuer-paid CRAs' information advantage helps predict accounting fraud.

Data Availability: Data are available from the public sources cited in the text.

JEL classifications: G24; K22; M41.

Keywords: accounting fraud; fraud prediction; credit rating agency; issuer-paid rating agency; investor-paid rating agency; F-score.

I. INTRODUCTION

Accounting fraud imposes significant costs on firms and their stakeholders, including higher costs of capital, inefficient resource allocation, regulatory sanctions, and investment losses (Dechow, Sloan, and Sweeney 1996; Hribar and Jenkins 2004; Graham, Li, and Qiu 2008; Karpoff, Lee, and Martin 2008; Dechow, Ge, and Schrand 2010; Kravet and Shevlin 2010). Not surprisingly, stakeholders, regulators, and researchers are interested in

We thank Daniel J. Taylor (editor), two anonymous referees, Dan Amiram, Jonathan Karpoff, Xiumin Martin, Yupeng Lin, Jeff Ng, Charles Shi, and the seminar participants at the European Accounting Association Congress, Verein für Socialpolitik, The Australian National University, City University of Hong Kong, Columbia University, Fudan University, The Hong Kong Polytechnic University, The Hong Kong University of Science and Technology, National University of Singapore, Peking University, Shanghai University of Finance and Economics, Tsinghua University, Xiamen University, The University of Hong Kong, The University of Manchester, and University of Mannheim. We thank Vicki Shen from S&P, Tina Xu from Moody's, and Karen Qian from Fitch Ratings for answering numerous questions. We thank Srijith Kannan, Lu Qiu, Hui Wang, Yirong Zou, and Alina Pugacheva for excellent research assistance. Shiheng Wang gratefully acknowledges the financial support received from the Hong Kong Research Grant Council (GRF:16513116). Pepa Kraft gratefully acknowledges funding received from the HEC Paris Foundation and the French National Research Agency (Ecodec ANR-11-LABX-0047).

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Editor's note: Accepted by Daniel J. Taylor, under the Senior Editorship of W. Robert Knechel.

Submitted: December 2021
Accepted: April 2023
Early Access: August 2023

accounting fraud detection. Prior academic studies have developed numerous models to predict fraud (Beneish 1997, 1999; Dechow, Ge, Larson, and Sloan 2011; Bao, Ke, Li, Yu, and Zhang 2020).[1] However, as one of the most important information intermediaries with unique access to material nonpublic information from management, credit rating agencies (CRAs) are largely missing from the fraud detection literature. Although studies document that CRAs give lower ratings to firms with more aggressive financial reporting, worse accruals quality, and less timely earnings (Ahmed, Billings, Morton, and Stanford-Harris 2002; Ashbaugh-Skaife, Collins, and LaFond 2006), they do not focus on fraud firms or examine whether rating actions are incrementally informative in predicting fraud beyond other public information sources, such as financial statements. Our study fills this void by examining the incremental usefulness of CRAs' rating actions for fraud prediction.

Ex ante, it is unclear whether CRAs' rating actions are incrementally informative about fraud. On the one hand, because issuer-paid CRAs have incentives to cater to issuers (Becker and Milbourn 2011; Jiang, Stanford, and Xie 2012; Griffin, Nickerson, and Tang 2013; Kraft 2015a), they may not take negative rating actions or may not incorporate fraud-related information into their ratings in a timely fashion. Indeed, both investors and regulators have criticized issuer-paid CRAs for failing to effectively assess financial reporting quality, especially in the wake of high-profile fraud cases in the early 2000s (Securities and Exchange Commission (SEC) 2003; Partnoy 2006; Frost 2007). The 2008 financial crisis sparked further debate on whether issuer-paid CRAs have the expertise to analyze complex transactions and products (Coval, Jurek, and Stafford 2009). Consistent with this view, Alissa, Bonsall, Koharki, and Penn (2013) and Jung, Soderstrom, and Yang (2013) find that debt issuers that manage earnings receive higher credit ratings, suggesting that CRAs do not fully recognize accounting manipulation. Additionally, CRAs want to keep ratings stable because of contracting or regulatory concerns (Beaver, Shakespeare, and Soliman 2006; Cheng and Neamtiu 2009; J. Cornaggia and K. Cornaggia 2013; Bruno, J. Cornaggia, and K. Cornaggia 2016).

On the other hand, CRAs have incentives to consider fraud in their ratings and have access to information that may systematically correlate with fraud. Regarding their incentives, the primary mission of CRAs is to predict default risk, which is exacerbated by fraud for two reasons. First, fraud can reduce firms' future cash flows by imposing various direct and indirect costs, such as litigation expenses, lost sales, and higher costs of capital (see Amiram et al. (2018) for a review). Second, fraud results in inaccurate financial statements that obscure firms' real performance and increase information asymmetry in the debt market (Graham et al. 2008; Wittenberg-Moerman 2008). Greater information asymmetry makes it more difficult to monitor management and increases agency costs (Jensen and Meckling 1976). It also increases information risk (Easley and O'Hara 2004), leading to higher default risk (Anderson, Mansi, and Reeb 2004; Cheng and Subramanyam 2008; Mansi, Maxwell, and Miller 2011). Concerning information availability, issuer-paid CRAs enjoy privileged access to management, according to nondisclosure agreements (Joynt 2002). For example, rated firms provide financial forecasts to rating analysts, grant them onsite visits to observe firm operations, and allow face-to-face meetings with top executives (Muddy Waters Research 2010; Brown, Call, Clement, and Sharp 2015). In sum, whether CRAs' rating actions are incrementally informative in predicting fraud is an empirical question.

To answer this question, we examine whether including the rating actions of Standard & Poor's (S&P) can improve fraud prediction models' performance. We use the *F-score* model by Dechow et al. (2011) as the primary benchmark because it is the most widely used fraud prediction model in the accounting literature (Baker, Purda, and Saadi 2020). To examine how private access to management among issuer-paid CRAs (e.g., S&P) affects the ability of their rating actions to predict fraud, we compare their rating actions with those of an investor-paid CRA, Egan-Jones Rating Company (EJR), which has limited access to firms' management and instead relies on public information (Beaver et al. 2006; Bruno et al. 2016; Bonsall, Koharki, and Neamtiu 2017; Ahn, Bonsall, and Buskirk 2019). Following the recommendation of Donelson, Kartapanis, McInnis, and Yust (2021), we use a sample of accounting frauds consisting of settled securities class action lawsuits alleging accounting misstatements and the SEC's Accounting and Auditing Enforce Releases (AAERs).

We find that individually, S&P's and EJR's rating actions are significantly and positively associated with fraud after controlling for *F-score* and information from other market participants, including short interest, equity returns, changes in equity analyst recommendations, and changes in credit default swap (CDS) spreads. Each CRA's rating actions also can improve the models' ability to predict fraud. However, when both are included in the model, only S&P's rating actions remain significant. In addition, whereas adding S&P's rating actions increases the explanatory power of the model that includes EJR's rating actions, the opposite is not true. This observation is consistent with EJR's reliance on public information, resulting in lower incremental informativeness of its rating actions for fraud prediction. Our results are robust to a variety of sensitivity tests, including expanding the sample to add firms covered by S&P but not EJR or

[1] We use "fraud prediction" and "fraud detection" interchangeably in the paper, both referring to the use of contemporaneous information to identify fraud firms before the public revelation of fraud.

frauds shorter than one year; limiting S&P's rating actions to downgrades only; benchmarking against the *M-score* from Beneish (1999), the litigation risk measure introduced by Kim and Skinner (2012), and alternative measures of *F-score*; controlling for firm fundamentals and industry fixed effects; and measuring the control variables using an alternative window. We further document that, consistent with the intuition from the literature on credit rating agencies (deHaan 2017), S&P's rating actions are more useful for fraud prediction after the 2008–2009 financial crisis.

We also conduct three sets of analyses to investigate when rating actions are most informative in fraud prediction. First, we examine the predictive ability of rating actions in different stages of fraud. We find that CRAs' rating actions are incrementally informative in predicting fraud during the last third of a fraud period. Specifically, S&P's rating actions predict fraud in the four quarters prior to fraud revelation, whereas EJR's rating actions do so only in the last two quarters. Second, we conduct a within-fraud-sample analysis to better control for other firm characteristics that may cause rating actions. We find evidence consistent with the first set of analyses that S&P takes negative rating actions against fraud firms as early as four quarters before fraud revelation, significantly earlier than EJR, which does not begin downgrading fraud firms until two quarters before fraud revelation. Third, we conduct a fraud-CRA-level analysis to quantify the timing differences between the two CRAs and find that S&P's earliest actions against fraud firms date roughly three to four months ahead of those of EJR.

This study contributes to three streams of literature. First, we add to the literature on fraud indicators and prediction models (Beneish 1997, 1999; Cecchini, Aytug, Koehler, and Pathak 2010; Dechow et al. 2011; Hobson, Mayew, and Venkatachalam 2012; Larcker and Zakolyukina 2012; Purda and Skillicorn 2015; Bao et al. 2020; Brown, Crowley, and Elliott 2020). We find that negative rating actions taken by issuer-paid CRAs are incrementally predictive of accounting fraud beyond well documented fraud indicators and that these actions occur as early as four quarters before fraud revelation. Our study, thus, has practical implications for investors and regulators in using rating actions to detect fraud in CRA-covered firms.

Second, our study contributes to the literature on fraud detection and revelation mechanisms. In this line of research, Dyck, Morse, and Zingales (2010) find that employees, the media, and industry regulators are the main whistleblowers of corporate fraud. Other studies show that sophisticated investors such as short sellers and banks incorporate fraud information into their decisions (Desai, Krishnamurthy, and Venkataraman 2006; Karpoff and Lou 2010; Chen 2016). Miller (2006) documents that the media covers 29 percent of fraud firms before a public fraud revelation by the firm or SEC. Our results indicate that S&P's rating actions are informative in predicting fraud, even after controlling for signals from financial statements, short sellers and other equity investors, financial analysts, and sophisticated investors in the debt market. These findings suggest that although CRAs do not claim to detect fraud, their rating actions could reveal fraud-related information.

Third, we add to the literature comparing the performance of issuer-paid and investor-paid CRAs. Studies document that issuer-paid CRAs are slower to downgrade firms' credit ratings than investor-paid CRAs due to conflicts of interest and concerns about the effects of rating changes on contracts and regulatory compliance (Beaver et al. 2006; Bolton, Freixas, and Shapiro 2012; Jiang et al. 2012; Cornaggia and Cornaggia 2013; Bruno et al. 2016; Bonsall et al. 2017). We show that the rating actions of issuer-paid CRAs are incrementally informative and quicker to predict fraud relative to those of investor-paid CRAs. Hence, our paper demonstrates that issuer-paid CRAs' access to material nonpublic information enables them to outperform investor-paid CRAs under certain conditions where access to private information is highly valuable.

II. INSTITUTIONAL BACKGROUND

CRAs view their primary mission as predicting default risk instead of exposing accounting fraud; therefore, credit ratings may have limited usefulness for predicting accounting fraud. For example, CRAs generally limit their legal liability by claiming that they are not active fraud detectors and depend primarily on information provided by firms (Securities and Exchange Commission (SEC) 2003). Consistent with this view, Alissa et al. (2013), Jung et al. (2013), and Liu, Shi, Subramanyam, and Zhang (2018) find that firms can maintain their favorable ratings or achieve rating upgrades by smoothing their earnings, managing their accruals upward, and pursuing real earnings management. Other studies, such as Lee (2012), find that CRAs cannot detect issuers' manipulations in cash flow classifications.

Even if issuer-paid CRAs acquire negative information related to accounting fraud, their relations with issuers and other market participants' reliance on ratings may delay the incorporation of this information into ratings. Most issuer-paid CRAs charge firms an origination fee and periodic monitoring fees. They also offer consulting services, such as pre-rating assessments (Bolton et al. 2012). These incentives may compel issuer-paid CRAs to give unduly favorable ratings (Griffin et al. 2013), especially to issuers from whom they derive substantial income (He, Qian, and Strahan 2012). Issuer-paid CRAs (S&P, Moody's, and Fitch) also may avoid premature downgrades and volatile ratings because such actions may trigger contract renegotiations and force frequent trading and adjustments to capital reserves in financial institutions (C. Opp, M. Opp, and Harris 2013). Consistent with this argument, Beaver et al. (2006) and Cornaggia and Cornaggia (2013) show that S&P and Moody's incorporate default risk into their ratings more slowly, compared to the investor-paid EJR and RapidRatings. These findings suggest that the usefulness of issuer-paid CRAs' credit ratings for fraud prediction may be constrained by their failure to incorporate fraud-related information into ratings in a timely manner.

However, CRAs have a unique advantage in obtaining accounting fraud information and incentives to account for this information in their rating actions. Firms' accounting fraud is relevant to their default risk. If exposed, the fraud can reduce firms' future cash flows. Unlike firms that engage in more benign forms of earnings management, fraud firms are more likely to incur direct costs (e.g., fines and penalties imposed by regulators), litigation expenses (e.g., legal fees and settlements), and higher directors' and officers' insurance premiums, as well as indirect costs such as lost sales, higher costs of capital, and reputational damage (see Amiram et al. (2018) for a review). Accounting fraud also leads to inaccurate financial statements, which increases information asymmetry in the debt market (Graham et al. 2008; Wittenberg-Moerman 2008). Greater information asymmetry hinders monitoring of management and increases agency costs (Jensen and Meckling 1976), and it exacerbates information risk (Easley and O'Hara 2004), leading to higher default risk (Anderson et al. 2004; Cheng and Subramanyam 2008; Mansi et al. 2011). Standard & Poor's (S&P) (2017) thus identifies financial transparency as one of its four major corporate governance characteristics when assigning credit ratings. Moody's has an accounting specialist group whose duties include looking for evidence of aggressive accounting and weak reporting controls (Moody's Investors Service 2007). Moody's and Fitch also have published reports highlighting weaknesses in accounting and financial reporting quality and their effects on ratings (Moody's Investors Service 2004, 2011; Jonas 2005; O'Keeffe 2011). Kraft (2015b) shows that Moody's considers aggressive accounting practices in its credit assessments.

Compared with other market participants, including investor-paid CRAs, issuer-paid CRAs enjoy a unique advantage in their ability to obtain material nonpublic information from firm management. For example, nondisclosure agreements between issuer-paid CRAs and rated firms give CRAs access to firms' credit and acquisition agreements, private placement memoranda, budgets, forecasts, and more detailed financial reporting, as well as advance notification of major events (Joynt 2002; Beasley, Branson, Pagach, and Panfilo 2021). Furthermore, issuer-paid CRAs conduct regular site visits (e.g., during their initial rating and annual reviews), during which they can observe and collect additional private information (Muddy Waters Research 2010; Brown et al. 2015; Cheng, Du, X. Wang, and Y. Wang 2016). For example, during these site visits, rating analysts often have face-to-face meetings with top executives, such as CEOs and chief financial officers (CFOs). Because these meetings are less rehearsed than public disclosures, firm managers' vocal cues and facial expressions can provide insight into their philosophies, personalities, and integrity (Mayew and Venkatachalam 2012; Blankespoor, Hendricks, and Miller 2017; Bushee, Jung, and Miller 2017; Park and Soltes 2018). In contrast, investors and equity analysts usually meet only with the investor relations team during site visits (Brown et al. 2015). Consistent with this argument and anecdotal evidence, Ahn et al. (2019) find that issuer-paid CRAs learn about bad news earlier than other market participants. Similarly, Bonsall et al. (2017) show that although issuer-paid CRAs issue less accurate, less informative, and less timely ratings than do investor-paid CRAs, issuer-paid CRAs underperform less for rated firms with high information uncertainty than for those with low information uncertainty, likely because investor-paid CRAs rely on public disclosure.

Note that we do not claim that issuer-paid CRAs directly observe or actively detect accounting fraud. Instead, we argue that issuer-paid CRAs have better access to information related to the incentives or symptoms of accounting fraud. As such, their rating actions may reflect this information and be incrementally informative in predicting fraud.[2]

III. SAMPLE SELECTION

Our sample period begins in July 1999 because EJR data are not available prior to that. We obtain S&P's long-term issuer ratings and credit watch from Compustat and EJR's ratings from Kraft, Xie, and Zhou (2020) (July 1999 to April 2012) and Bloomberg (May 2012 to December 2018).[3] We convert letter ratings to numerical values using an ordinal scale ranging from 1 for the lowest rated firms (D) to 21 for the highest rated firms (AAA).

[2] To better understand issuer-paid CRAs' unique position in accessing private information and their incentives, we interview several people working for issuer-paid CRAs, including the head of one of the top three rating agencies in the Asia-Pacific region and several rating analysts. During the interviews, the respondents confirm that issuer-paid CRAs have more access to corporate information than do other information intermediaries. Furthermore, CRAs care about accounting fraud because fraud increases a firm's default risk. As such, issuer-paid CRAs often request additional information if they are concerned about the quality of any reported accounting numbers.

[3] Bloomberg's coverage of EJR ratings begins in 2011. We compare EJR's ratings from both sources during the overlap period (i.e., 2011 to April 2012) and confirm that they have the same coverage and ratings. EJR data from both sources include only rating downgrades, upgrades, and affirmations.

We construct the fraud sample using SEC's AAERs and the securities class action lawsuits from the Securities Class Action Clearinghouse (SCAC) database. We use these two types of enforcement following the recommendation of Donelson et al. (2021), who show that both are valid proxies for accounting fraud and that "using only public or private enforcement excludes fraud observations, leading to biased regression estimates and reduced power."[4]

As our main objective is to examine the ability of rating actions to depict accounting fraud before it is publicly revealed, we focus on the period from the fraud start date until the initial public revelation date (Karpoff and Lou 2010). For SCAC cases, we define the start of the fraud period as the class period begin date and the initial fraud revelation date as the class period end date when a corrective disclosure is usually made either by the firm or information intermediaries, such as analysts and journalists (Booth 2012).[5] For AAER cases, we use the misstatement period begin date as the start of the fraud period and manually search all press releases and news in Factiva to identify the fraud revelation date.[6]

Table 1 presents our data selection procedures. For the securities class action lawsuits, we start with 2,388 settled cases that allege violations of Section 10(b) of the 1934 Securities Exchange Act (manipulative and deceptive devices). We exclude dismissed cases because they are less likely to be based on credible fraud allegations (Donelson et al. 2021). From this sample, we exclude 499 cases with a class period ending before July 1999 or after December 2018, 254 cases for which we are unable to find Compustat or CRSP identifiers for the firms involved, and 220 cases involving financial firms (i.e., two-digit SIC codes 60–69) or firms without industry information. Next, we remove 1,147 cases not covered by either S&P or EJR during the two years before the fraud revelation to ensure that any differences in the rating actions of the two CRAs are not driven by differences in the firms they cover. We further drop 23 cases without sufficient data to calculate the required variables for our analyses.

From the remaining 245 cases, we read case descriptions and complaints to exclude those that allege only false forward-looking statements or nonaccounting malpractice (79) to focus on allegations of misstatements related to GAAP violations (Amiram et al. 2018).[7] We also exclude 41 cases with class periods of less than one year because CRAs usually review financial statements annually and are thus less likely to acquire sufficient information within such a short duration.[8] Our final sample of securities class action lawsuits includes 125 cases.

For the AAERs, we start with 1,657 unique cases from an initial sample of 4,012 AAER filings. Similar to the procedures used for the SCAC cases, we first remove 1,123 cases with fraud committed outside our sample period or without fraud period information, 102 for which we are unable to find Compustat or CRSP identifiers for the firms involved, and 75 involving financial firms or firms without industry information. Next, we exclude 263 cases that do not have credit ratings from either S&P or EJR before the fraud revelation, two with missing data for the required variables, and four with a fraud period of less than one year. Among the remaining 88 cases, 36 are already included in the sample of securities class action lawsuits. Thus, our final AAER sample includes 52 additional unique accounting fraud events. Combined, our full sample includes 177 unique accounting fraud events where fraud firms are covered by both S&P and EJR.

Untabulated descriptive statistics show that our sample fraud events peak in frequency during the 2002–2004 period, possibly reflecting enactment of the Sarbanes-Oxley Act and the bursting of the dot-com bubble. We also observe that the industry distribution of sample firms is generally comparable with that of the universe of firms in Compustat covered by both S&P and EJR. The mean durations of SCAC and AAER cases from the beginning of fraud

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4 We do not include restatements (e.g., from Audit Analytics) because Donelson et al. (2021) conclude that "many of these restatements lack credible fraud allegations from public or private enforcement and appear to be false positive" and that "relatively few of these restatements appear relevant for researchers interested in accounting fraud."

5 An alternative measure of the initial fraud revelation date for securities class action lawsuits is the lawsuit filing date, which follows the end of the class period. We do not use the filing date for two reasons. First, stocks usually have more negative returns on the class period end date than on the lawsuit filing date. In our fraud sample, the means (medians) of the three-day market-adjusted returns centered on the class period end dates and the filing dates are −23.35 percent (−19.36 percent) and −7.81 percent (−2.31 percent), respectively. Thus, it is likely that at least some fraud information is revealed on the class period end date. Second, although the public may not know the full extent of the fraud until after the class period ends, using a later date would bias the results toward finding that CRAs take rating action before fraud revelation.

6 For each AAER case, we search for the following terms during the window from the fraud commitment period end date to the AAER release date (if a case has multiple AAER filings, we use the earliest release date): "accounting," "audit," "financial," "GAAP," "fraud," "illegal," "illicit," "doubtful," "dubious," "suspicious," "false," "falsify," "improper," "irregular," "irregularity," "misrepresent," "misrepresentation," "misappropriate," "overstate," "inflate," "understate," "adjust," "adjustment," "restate," "restatement," "violate," "violation," "mislead," "misleading," "write-off," "discrepancy," "misstatement," "revenue recognition," "insider trading," "investigate," "probe," "quit," "quitting," "resign," "rumor," "lawsuit," "opinion withdraw," and "short sell." We read each resulting article to identify the earliest article that may indicate fraud. In untabulated analyses, we find similar results when we use the misstatement period end date instead of the fraud revelation date to define the end of the fraud period for AAER.

7 Two of this study's authors independently read the detailed case descriptions and related complaints to determine whether each case involves misstatements of accounting numbers in financial statements, misleading forward-looking disclosures, or nonaccounting malpractice, such as bribery or allegations against equity analysts or underwriters. They then discuss and reconcile any differences in their classifications.

8 In an untabulated sensitivity test, we confirm that our results hold when we include frauds shorter than one year.

TABLE 1

Sample Selection Procedures

	SCAC	AAERs
# of settled cases from SCAC involving allegations of violation of Rule 10 b-5 (# of unique fraud events from AAERs)	2,388	1,657
Less: Fraud events that end before July 1, 1999 or after December 31, 2018	(499)	(1,123)
	1,889	534
Less: Fraud firms without Compustat GVKEY or CRSP PERMNO	(254)	(102)
	1,635	432
Less: Fraud firms in the financial industry or without industry information (6000 ≤ SIC ≤ 6999)	(220)	(75)
	1,415	357
Less: Fraud firms not covered by S&P or EJR before the fraud revelation	(1,147)	(263)
	268	94
Less: Fraud firms with missing data for the *F-score* and control variables	(23)	(2)
	245	92
Less: SCACs alleging false and misleading disclosures or other nonaccounting issues	(79)	
	166	
Less: Fraud events that last less than 1 year	(41)	(4)
# of fraud events	**125**	**88**
Combining two types of fraud events		
# of SCACs	125	
# of *additional* unique fraud events from AAERs	52	
Total # of unique accounting fraud events	**177**	

This table presents the procedures used to select our sample of accounting fraud events from the Securities Class Action Clearinghouse (SCAC) and Accounting and Auditing Enforcement Releases (AAERs) databases.

until public revelation are 11.51 and 16.25 quarters, respectively. The difference in fraud durations suggests that public and private enforcement actions reflect different priorities in selecting fraud cases to prosecute, highlighting the importance of including both types of enforcement when identifying fraud (Donelson et al. 2021).

IV. USEFULNESS OF RATING ACTIONS FOR ACCOUNTING FRAUD PREDICTION

Predictability of Rating Actions for Accounting Fraud

To assess whether rating actions are useful for fraud prediction, we estimate the following fraud prediction model at the firm-quarter level:

$$Prob(Fraud = 1) = \alpha + \beta \cdot RatingActions + \delta \cdot F\text{-}score + \gamma \cdot MarketSignals + \varepsilon, \tag{1}$$

where *Fraud* is an indicator variable representing firm-quarters after fraud starts but before it is revealed. *RatingActions* includes *Action_SP*, an indicator variable that equals 1 if S&P issues a rating downgrade or places the firm on negative credit watch in a firm-quarter, and 0 otherwise, and *Action_EJR*, an indicator variable that equals 1 if EJR issues a rating downgrade in a firm-quarter, and 0 otherwise. When measuring negative rating actions, we consider both rating downgrades and negative credit watches for S&P for two reasons. First, prior studies suggest that CRAs' monitoring role is "most apparent in their credit watch procedures" (Boot, Milbourn, and Schmeits 2006). Second, S&P's negative credit watch actions provide as much information to the market as do downgrades by EJR.[9]

[9] Based on the universe of firms covered by both S&P and ERJ during our sample period, the three-day abnormal return centered on S&P's negative credit watch date is −4.99 percent, which is not significantly different from that of a one-notch downgrade by EJR (−5.69 percent). However, a one-notch downgrade by S&P leads to only a three-day abnormal return of −4.25 percent, which is smaller than that of EJR (significant at the 5 percent level), possibly because many S&P downgrades are preceded by negative credit watch actions. We find similar results using a regression analysis that includes firm and year fixed effects to control for time-invariant firm characteristics and macroeconomic factors that may affect both negative rating actions and stock returns.

We measure *F-score* using Model 2 of Dechow et al. (2011). Following previous studies (e.g., Price, Sharp, and Wood 2011; Beneish and Vorst 2022), we use the coefficient estimates of Dechow et al. (2011) to combine the components of *F-score*. *MarketSignals* includes a firm's abnormal short interest (Karpoff and Lou 2010) and current quarter's and previous year's market-adjusted buy-and-hold returns (*ABSI*, *RET*, and *Prior_RET*, respectively), which capture information available from equity markets, as well as changes in analysts' recommendations (ΔREC) and five-year-maturity CDS spreads (ΔCDS), which capture information of financial analysts and debtholders. For firm-quarters with rating actions, to exclude market reactions to rating actions, we measure *ABSI*, *RET*, ΔREC, and ΔCDS over the 91-day window that ends two days before the earliest rating action and *Prior_RET* during the one year before this window.[10] We obtain stock price and return data from CRSP, accounting and short interest data from Compustat, analyst recommendations from I/B/E/S, and CDS spreads from Markit. The Appendix A provides detailed definitions of the variables. We use logistic regressions and report the z-statistics based on standard errors clustered by firm and year.[11] Our sample includes 1,597 fraud firm-quarters of the 177 frauds and 44,418 nonfraud firm-quarters between July 1999 and December 2018.

Untabulated summary statistics of the fraud- and nonfraud firm-quarters show that compared with nonfraud firm-quarters, fraud firm-quarters are more likely to receive negative rating actions from both S&P and EJR, providing preliminary evidence that rating actions may contain fraud-related information. In line with previous studies (Karpoff and Lou 2010; Dechow et al. 2011; Kim and Skinner 2012), fraud firms also have a higher *F-score* and abnormal short interest, more negative stock returns, more analyst downgrades, and a greater increase in CDS spreads than nonfraud firms.

Table 2, Panel A presents the estimation of the fraud prediction models. We start with a baseline model of only *F-score* in column (1), which shows a positive and significant coefficient, consistent with Dechow et al. (2011). In addition to evaluating the statistical significance of the coefficients, we follow previous studies and use the area under the receiver operating characteristic (ROC) curve (AUC) to measure the models' ability to differentiate fraud and nonfraud observations (Kim and Skinner 2012; Larcker and Zakolyukina 2012). The AUC of the baseline model is 0.587, which suggests that the model has moderate power to distinguish fraud from nonfraud firm-quarters and highlights the difficulty of fraud prediction in this sample. Note that the AUC may not be directly comparable with prior studies that use *F-score* for two reasons. First, the definition of fraud differs across studies. As discussed, we follow the recommendation of Donelson et al. (2021) and use both public and private enforcement.[12] Second, as our paper focuses on the fraud predictability of CRAs' rating actions, we require that the sample firms be covered by both S&P and EJR. Nonetheless, the AUC is within the range of the AUCs of *F-score*-only models (0.53–0.68) reported in previous studies.[13]

Next, we separately include S&P's and EJR's rating actions in the model to examine whether incorporating either rating actions improves the model's ability to distinguish between fraud and nonfraud observations. As tabulated in Table 2, Panel A, columns (2) and (3), both rating actions are positive and significant when individually added to the baseline model (both at the 1 percent level), consistent with these rating actions indicating a higher likelihood of fraud. The AUCs of the models supplemented with S&P's and EJR's rating actions are 0.605 and 0.596, representing 1.8- and 0.9-percent improvements over the baseline model, respectively (Chi-square tests show both as statistically significant at the 1 percent level). As benchmarks, in untabulated analysis, individually adding abnormal short interest, current and prior returns, change in equity analyst recommendations, or change in CDS spreads to the baseline model increases the AUC by 2.8, 0.7, 0.7, and 0.1 percent, respectively (significant at the 1 percent level for short interest and change in analyst recommendations and at the 10 percent level for returns and change in CDS spreads). The increase in AUC is also comparable with prior studies. For instance, Bao et al. (2020) show that using 28 raw financial data items and an ensemble learning model improves the AUC of the Dechow et al. (2011) style model (14 financial ratios and logistic regression) by 1.5 percent for the 2003–2014 period (0.702–0.717, in Bao et al. (2020, Table 5)). Taken together, CRAs' rating actions are incrementally informative in predicting undisclosed fraud, with an economic magnitude between those of financial analysts and short sellers.

We add both CRAs' rating actions to the baseline model and find that those of S&P and EJR are significant at the 1 and 10 percent levels, respectively, in Table 2, Panel A, column (4). A comparison of the AUCs across models shows a similar pattern: adding rating actions improves the model's ability to discern fraud observations, as can be seen by comparing column (4) with column (1). Nonetheless, most of the discriminative ability originates from S&P's rating actions:

[10] As a robustness check, we measure *MarketSignals* until the end of every firm-quarter and find similar results (untabulated).

[11] Following prior fraud studies (e.g., Dechow et al. 2011; Hobson et al. 2012; Larcker and Zakolyukina 2012; Bao et al. 2020; Brown et al. 2020), we do not include fixed effects. In untabulated sensitivity tests, we find similar results when including industry fixed effects.

[12] For example, Larcker and Zakolyukina (2012, Table 9) report that *F-score*'s AUC values are 0.527, 0.529, 0.537, and 0.701 when financial frauds are defined as restatements, irregularities or accounting issues, irregularities, and AAERs, respectively (reported in their Table 9).

[13] For example, Larcker and Zakolyukina (2012, Table 9), Purda and Skillicorn (2015, Table 4), Perols, Bowen, Zimmermann, and Samba (2017, Table 3), Alawadhi, Karpoff, Kosk, and Martin (2020, Figure 1), Bao et al. (2020, Table 3), and Beneish and Vorst (2022, Table 2).

TABLE 2

Predictability of Rating Actions for Accounting Fraud

Panel A: Regression Analyses

Dep. Var. =	*Prob (Fraud = 1)*							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
F-score	0.553***	0.562***	0.558***	0.564***	0.575***	0.580***	0.578***	0.582***
	(3.15)	(3.21)	(3.19)	(3.22)	(3.32)	(3.34)	(3.33)	(3.35)
Action_SP		**0.640*****		**0.565*****		**0.520*****		**0.475*****
		(3.61)		**(3.36)**		**(3.29)**		**(3.06)**
Action_EJR			**0.395*****	**0.250***			**0.277****	0.167
			(2.70)	**(1.93)**			**(2.20)**	(1.41)
ABSI					5.483***	5.256***	5.378***	5.209***
					(3.04)	(2.87)	(2.98)	(2.85)
RET					−0.720*	−0.614	−0.646	−0.577
					(−1.72)	(−1.58)	(−1.61)	(−1.51)
Prior_RET					−0.018	0.036	0.008	0.047
					(−0.09)	(0.18)	(0.04)	(0.23)
Δ*REC*					−0.688***	−0.670***	−0.676***	−0.664***
					(−4.61)	(−4.73)	(−4.64)	(−4.75)
Δ*CDS*					3.652	2.709	3.318	2.583
					(1.02)	(0.88)	(0.96)	(0.86)
AUC	0.587	0.605	0.596	0.608	0.624	0.633	0.627	0.634
		(2) versus (1)	(3) versus (1)	(4) versus (1)	(5) versus (1)	(6) versus (5)	(7) versus (5)	(8) versus (5)
		0.018**	***0.009*****	***0.021*****	***0.037*****	***0.009*****	***0.003****	***0.010*****
		(21.58)	***(10.00)***	***(27.20)***	***(52.48)***	***(13.87)***	***(3.57)***	***(16.22)***
				(4) versus (2)				(8) versus (6)
Incremental AUC (Chi-square)				***0.003******				*0.001*
				(4.57)				*(1.61)*
				(4) versus (3)				(8) versus (7)
				0.012**				***0.007*****
				(14.42)				***(11.83)***
# of fraud quarters	1,597	1,597	1,597	1,597	1,597	1,597	1,597	1,597
# of nonfraud quarters	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418

(continued on next page)

TABLE 2 (continued)

Panel B: Fraud Prediction Performance—Fraud Score Cutoff Set at 1

	F-score Predicted			*F-score* and *Action_SP Predicted*			*F-score* and *Action_EJR Predicted*		
Observed	**Fraud (1)**	**Nonfraud (2)**	**Total (3)**	**Fraud (4)**	**Nonfraud (5)**	**Total (6)**	**Fraud (7)**	**Nonfraud (8)**	**Total (9)**
# Fraud firm-quarters	989	608	1,597	1,018	579	1,597	978	619	1,597
# Nonfraud firm-quarters	20,433	23,985	44,418	19,331	25,087	44,418	19,960	24,458	44,418
Total	21,422	24,593	46,015	20,387	25,628	46,015	20,938	25,077	46,015
%Fraud firm-quarters	61.93	38.07	3.47	63.99	36.01	3.47	61.24	38.76	3.47
%Nonfraud firm-quarters	46.00	54.00	96.53	43.60	56.40	96.53	44.94	55.06	96.53
Correct Classification (%)		54.27			56.73			55.28	
Sensitivity (%)		61.93			63.74			61.24	
Type I errors (%)		46.00			43.52			44.94	
Type II errors (%)		38.07			36.26			38.76	

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

This table presents the usefulness of credit rating actions for accounting fraud prediction. Panel A presents the regression analyses. Panel B compares the fraud prediction performance between models with only *F-score* components and those with both *F-score* components and rating actions. Standard errors are clustered by firm and year.

Correct Classification = (# of correctly classified fraud firm-quarters + # of correctly classified nonfraud firm-quarters)/# of total firm-quarters;

Sensitivity = # of correctly classified fraud firm-quarters/# of fraud firm-quarters; *Type I errors* = # of misclassified nonfraud firm-quarters/# of nonfraud firm-quarters; and *Type II errors* = # of misclassified fraud firm-quarters/# of fraud firm-quarters.

Variable definitions are presented in the Appendix A.

the difference between the AUCs of columns (4) and (2) is much smaller than that between the AUCs of columns (4) and (3). In columns (5)–(8), we control for information from other capital market participants and find a consistent pattern, that is, only S&P's rating actions can improve the model's ability to predict fraud, whereas those of EJR provide limited information beyond *F-score* and other capital market participants.[14]

To further gauge rating actions' incremental predictability for accounting fraud, we evaluate how incorporating them changes the model's sensitivity and type I and type II errors. We calculate the fraud score of each firm-quarter as the estimated fraud probability divided by the unconditional fraud probability of our sample (i.e., 3.47 percent = 1,597/46,015). Following Dechow et al. (2011), firm-quarters with a fraud score above (below) 1 are classified as fraud (nonfraud) firm-quarters. We consider four measures of model performance: (1) correct classification, the proportion of correctly classified firm-quarters; (2) sensitivity, the proportion of correctly classified fraud firm-quarters; (3) type I errors, the proportion of misclassified nonfraud firm-quarters; and (4) type II errors, the proportion of misclassified fraud firm-quarters.

We compare the models with and without rating actions in Table 2, Panel A, columns (1)–(3) and tabulate the results in Table 2, Panel B.[15] First, we observe that adding S&P's rating actions to *F-score*-only model improves the correct classification rate and sensitivity by 2.46 percent (= 56.73 − 54.27 percent) and 1.81 percent (= 63.74 − 61.93 percent), respectively, and reduces type I and type II errors by 2.48 percent (= 46.00 − 43.52 percent) and 1.81 percent (= 38.07 − 36.26 percent), respectively. To put these statistics in perspective, these improvements are larger than those gained by adding off-balance-sheet and nonfinancial variables (from Model 1 to Model 2 in Dechow et al. (2011)), which increase accuracy and sensitivity by 0.35 and 1.31 percent, respectively, and reduce type I errors by 0.36 percent (Table 7, Panel C of Dechow et al. (2011)).[16] Next, we find mixed evidence on the benefit of EJR's rating actions. Specifically, although adding EJR's rating actions to the *F-score*-only model improves the correct classification rate and reduces type I errors (both by about 1 percent), it exacerbates the sensitivity and type II errors (both by 0.7 percent). In sum, these results are consistent with the notion that S&P's, but not EJR's, rating actions are useful for fraud prediction, echoing those in Table 2, Panel A.

Predictability of Rating Actions for Accounting Fraud—Additional Analyses

We conduct four sets of additional analyses to explore the robustness and generalizability of our results. First, we test whether our results hold for a larger sample of firms. Our primary analyses require that firms be covered by both S&P and EJR so that we can compare the predictability of issuer-paid and investor-paid CRAs' rating actions for accounting fraud. In this test, we only require that firms be covered by S&P, which increases our fraud sample from 177 cases to 240 cases and the total number of firm-quarters in the tests from 46,015 (1,389 unique firms) to 82,700 (2,781 unique firms). Table 3, Panel A confirms that S&P's rating actions have incremental predictive power beyond the *F-score* in this sample.

Second, we consider both rating downgrades and negative credit watches for S&P in defining negative rating actions for our main tests because CRAs' monitoring role is "most apparent in their credit watch procedures" (Boot et al. 2006), and S&P's negative credit watch actions provide as much information to the market as do downgrades by EJR. In this robustness test, we use S&P's rating downgrades only. Table 3, Panel B presents similar results as in our main analyses, albeit with smaller increases in AUCs.

Third, we use the *F-score* in Model 2 of Dechow et al. (2011) as the main benchmark because it has higher accuracy than Models 1 and 3 (Table 7, Panel C of Dechow et al. (2011)). In this robustness test, we use Model 3 of Dechow et al. (2011), which adds market-based variables to Model 2 as an alternative benchmark. We find similar results (tabulated in Table 3, Panel C). Untabulated tests show that our results also are robust to using only annual data to calculate the three models of *F-score* and to using our own sample to re-estimate the coefficients on the *F-score* components and then recalculate the three models of *F-score*.

Fourth, we omit firm characteristics from the fraud prediction models to make our results more comparable with prior studies (e.g., Hobson et al. 2012; Larcker and Zakolyukina 2012; Brown et al. 2020; Beneish and Vorst 2022) and because the *F-score* likely already captures firm characteristics that are useful for fraud prediction. Nonetheless, in this robustness test, we additionally control for interest coverage (*INTCOV*), profitability (*PM*), total leverage (*LEV*), firm

[14] Diagnostic tests indicate that multicollinearity is not a concern in these models: the variance inflation factors are 1.05 and 1.03 in columns (4) and (8), respectively, below the usual threshold (Lennox, Francis, and Wang 2012).

[15] We obtain similar results after adding other market participants (*MarketSignals*) in the prediction models (untabulated).

[16] Adding off-balance-sheet and nonfinancial variables worsens the model's type II errors (from 31.38 percent to 32.07 percent). Similarly, adding stock market-based variables (i.e., from Model 2 to Model 3 in Dechow et al. (2011)) worsens the model's accuracy, specificity, and type I and II errors.

TABLE 3

Predictability of Rating Actions for Accounting Fraud—Robustness Tests

Panel A: Predictability of Rating Actions for Accounting Fraud—Firms Covered by S&P

Dep. Var. =	*Prob (Fraud = 1)*			
	(1)	**(2)**	**(3)**	**(4)**
F-score	0.564***	0.572***	0.579***	0.584***
	(4.37)	(4.45)	(4.55)	(4.59)
Action_SP		**0.581*****		**0.456*****
		(3.66)		**(3.34)**
ABSI			5.395***	5.241***
			(4.28)	(4.12)
RET			−0.777***	−0.698**
			(−2.61)	(−2.53)
Prior_RET			0.006	0.044
			(0.04)	(0.31)
ΔREC			−0.608***	−0.593***
			(−6.83)	(−6.99)
ΔCDS			2.533	1.768
			(0.89)	(0.74)
AUC	0.593	0.605	0.633	0.640
Incremental AUC (Chi-square)		(2) versus (1)	(3) versus (1)	(4) versus (3)
		0.012***	***0.040******	***0.007******
		(22.73)	***(92.60)***	***(13.90)***
# of fraud quarters	2,271	2,271	2,271	2,271
# of nonfraud quarters	80,429	80,429	80,429	80,429

Panel B: Predictability of Rating Downgrades for Accounting Fraud

Dep. Var. =	*Prob (Fraud = 1)*			
	(1)	**(2)**	**(3)**	**(4)**
F-score	0.575***	0.579***	0.578***	0.581***
	(3.32)	(3.34)	(3.33)	(3.35)
Downgrade_SP		**0.434*****		**0.378*****
		(3.16)		**(2.87)**
Action_EJR			**0.277****	**0.220***
			(2.20)	**(1.80)**
ABSI	5.483***	5.317***	5.378***	5.251***
	(3.04)	(2.92)	(2.98)	(2.89)
RET	−0.720*	−0.647	−0.646	−0.597
	(−1.72)	(−1.60)	(−1.61)	(−1.51)
Prior_RET	−0.018	0.019	0.008	0.036
	(−0.09)	(0.10)	(0.04)	(0.18)
ΔREC	−0.688***	−0.672***	−0.676***	−0.664***
	(−4.61)	(−4.66)	(−4.64)	(−4.67)
ΔCDS	3.652	3.077	3.318	2.866
	(1.02)	(0.95)	(0.96)	(0.91)
AUC	0.624	0.629	0.627	0.630
Incremental AUC (Chi-square)		(2) versus (1)	(3) versus (1)	(4) versus (1)
		0.005***	***0.003****	***0.006******
		(6.63)	***(3.57)***	***(9.84)***

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TABLE 3 (continued)

Dep. Var. =	***Prob (Fraud = 1)***			
	(1)	**(2)**	**(3)**	**(4)**
				(4) versus (2)
				0.001
				(2.38)
				(4) versus (3)
				0.003*
				(5.58)
# of fraud quarters	1,597	1,597	1,597	1,597
# of nonfraud quarters	44,418	44,418	44,418	44,418

Panel C: Predictability of Rating Actions for Accounting Fraud—*F-score* Based on Model 3 in Dechow et al. (2011)

Dep. Var. =	***Prob (Fraud = 1)***			
	(1)	**(2)**	**(3)**	**(4)**
F-score (Model 3)	0.558***	0.569***	0.565***	0.573***
	(3.09)	(3.15)	(3.14)	(3.18)
Action_SP		**0.557*****		**0.490*****
		(3.13)		**(2.88)**
Action_EJR			**0.351****	**0.226***
			(2.49)	**(1.79)**
ABSI	5.645***	5.384***	5.499***	5.316***
	(3.14)	(2.94)	(3.05)	(2.90)
Δ*REC*	−0.727***	−0.700***	−0.704***	−0.687***
	(−4.34)	(−4.44)	(−4.40)	(−4.49)
Δ*CDS*	4.538	3.436	4.054	3.235
	(1.21)	(1.07)	(1.14)	(1.03)
AUC	0.621	0.632	0.626	0.634
Incremental AUC (Chi-square)		(2) versus (1)	(3) versus (1)	(4) versus (1)
		0.011**	***0.005****	***0.013*****
		(14.98)	***(5.75)***	***(19.41)***
				(4) versus (2)
				0.002*
				(3.42)
				(4) versus (3)
				0.008**
				(12.04)
# of fraud quarters	1,580	1,580	1,580	1,580
# of nonfraud quarters	44,187	44,187	44,187	44,187

Panel D: Predictability of Rating Actions for Accounting Fraud—Controlling for Firm Characteristics

Dep. Var. =	***Prob (Fraud = 1)***			
	(1)	**(2)**	**(3)**	**(4)**
F-score	0.361	0.368	0.363	0.369
	(1.34)	(1.36)	(1.35)	(1.36)
Action_SP		**0.418*****		**0.397*****
		(2.86)		**(2.78)**
Action_EJR			0.172	0.089
			(1.42)	(0.78)

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TABLE 3 (continued)

Dep. Var. =	*Prob (Fraud = 1)*			
	(1)	**(2)**	**(3)**	**(4)**
ABSI	4.168**	4.097**	4.133**	4.081**
	(2.09)	(2.04)	(2.08)	(2.04)
RET	−0.301	−0.234	−0.262	−0.217
	(−0.89)	(−0.72)	(−0.79)	(−0.67)
Prior_RET	0.112	0.145	0.124	0.149
	(0.54)	(0.71)	(0.60)	(0.73)
ΔREC	−0.630***	−0.619***	−0.624***	−0.616***
	(−4.36)	(−4.46)	(−4.40)	(−4.51)
ΔCDS	2.490	1.861	2.318	1.802
	(1.01)	(0.89)	(0.99)	(0.89)
INTCOV	−0.001	−0.001	−0.001	−0.001
	(−0.27)	(−0.26)	(−0.25)	(−0.25)
PM	0.284	0.360	0.326	0.378
	(0.38)	(0.48)	(0.44)	(0.50)
LEV	0.326	0.289	0.312	0.284
	(0.68)	(0.61)	(0.65)	(0.59)
SIZE	0.154	0.151	0.152	0.150
	(1.62)	(1.59)	(1.59)	(1.57)
DEDT/EBITDA	0.005**	0.005**	0.005**	0.005**
	(2.09)	(2.09)	(2.10)	(2.10)
EARNVOL	0.261	0.264	0.255	0.261
	(0.60)	(0.61)	(0.59)	(0.60)
CASH	−0.699	−0.664	−0.693	−0.663
	(−0.48)	(−0.46)	(−0.48)	(−0.46)
TANG	−1.285	−1.283	−1.284	−1.282
	(−1.51)	(−1.50)	(−1.50)	(−1.50)
CAPEX	3.773	3.783	3.711	3.750
	(1.32)	(1.33)	(1.29)	(1.32)
Q	−0.266	−0.262	−0.265	−0.261
	(−1.22)	(−1.21)	(−1.22)	(−1.21)
RETEARN	−0.410*	−0.418*	−0.415*	−0.420*
	(−1.74)	(−1.78)	(−1.75)	(−1.79)
RETVOL	0.061	0.048	0.058	0.047
	(0.82)	(0.66)	(0.77)	(0.64)
BETA	0.167***	0.171***	0.167***	0.170***
	(2.77)	(2.83)	(2.77)	(2.83)
# of fraud quarters	1,597	1,597	1,597	1,597
# of nonfraud quarters	44,418	44,418	44,418	44,418

Panel E: Predictability of Rating Actions for Accounting Fraud—Alternative Benchmarks

Dep. Var. =	*Prob (Fraud = 1)*							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
KS	0.436***	0.444***	0.438***	0.444***				
	(3.28)	(3.35)	(3.29)	(3.35)				
M-score					0.113	0.139	0.128	0.145
					(0.63)	(0.81)	(0.73)	(0.84)
Action_SP		**0.664*****		**0.598*****		**0.640*****		**0.591*****
		(3.90)		**(3.72)**		**(3.80)**		**(3.57)**

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TABLE 3 (continued)

Dep. Var. =	***Prob (Fraud = 1)***							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Action_EJR			**0.371****	**0.220***			**0.314****	0.159
			(2.52)	**(1.66)**			**(2.51)**	(1.39)
AUC	0.591	0.601	0.593	0.602	0.512	0.538	0.523	0.543
Incremental AUC		(2) versus (1)	(3) versus (1)	(4) versus (1)		(6) versus (5)	(7) versus (5)	(8) versus (5)
(Chi-square)		***0.010****	*0.002*	***0.011****		***0.026****	***0.011****	***0.031****
		(10.57)	*(1.40)*	***(10.93)***		***(21.24)***	***(3.86)***	***(20.47)***
				(4) versus (2)				(8) versus (6)
				0.001				*0.005*
				(0.17)				*(1.65)*
				(4) versus (3)				(8) versus (7)
				0.009*				***0.020****
				(9.20)				***(18.15)***
# of fraud quarters	1,565	1,566	1,567	1,568	1,312	1,312	1,312	1,312
# of nonfraud quarters	43,893	43,894	43,895	43,896	38,117	38,117	38,117	38,117

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table presents the robustness tests on the usefulness of credit rating actions for accounting fraud prediction. Panel A presents rating actions' ability to predict accounting fraud for firm-quarters covered by S&P. Panel B presents rating downgrades' ability to predict accounting fraud. Panel C presents the results using the *F-score* from Dechow et al.'s (2011) Model 3 in the fraud prediction models. Panel D presents the results controlling for firm characteristics. Panel E presents the results using Kim and Skinner's (2012) litigation risk measure and Beneish's (1999) *M-score* as alternative benchmarks. Standard errors are clustered by firm and year.
Variable definitions are presented in the Appendix A.

size (*SIZE*), debt-to-EBITDA (*DEBT/EBITDA*), earnings volatility (*EARNVOL*), cash and marketable securities (*CASH*), tangibility (*TANG*), capital expenditure (*CAPEX*), Tobin's Q (*Q*), retained earnings (*RETEARN*), return volatility (*RETVOL*), and firm risk (*BETA*) in the fraud prediction models. Table 3, Panel D shows that S&P's rating actions remain significant in predicting fraud, but *F-score* loses its predictive power.[17]

Fifth, we use two other fraud indicators as benchmarks. Specifically, we use the *ex ante* litigation risk measure from Kim and Skinner (2012) and the *M-score* from Beneish (1999). We continue to find that S&P's rating actions have incremental predictive ability beyond these fraud indicators (tabulated in Table 3, Panel E).

Finally, we explore whether rating actions can better predict fraud after the 2008–2009 financial crisis. The crisis sparked debate on CRAs' expertise and conflict of interests (Coval et al. 2009). In response, the U.S. Congress passed the Dodd-Frank Act of 2010, which significantly increased CRAs' liability by making it easier for the SEC to impose sanctions on and bring claims against CRAs for materially misstated ratings and for investors to sue CRAs. The extent literature finds mixed evidence on the effect of the Act on rating quality: whereas deHaan (2017) documents that S&P and Moody's reduce type II errors and improve the timeliness of rating actions against firms that subsequently default, Dimitrov, Palia, and Tang (2015) find that rating actions become less informative to investors. In this analysis, we classify our sample into pre- and post-crisis periods based on the National Bureau of Economic Research date (whether the firm-quarter end is before or after June 30, 2009; National Bureau of Economic Research (NBER) 2023) and investigate whether rating actions are more useful for fraud prediction in the post-crisis period. We do so using two research designs. First, we estimate the fraud prediction model in Equation (1) separately for these two subperiods. Second, we estimate a pooled model including the interaction of the indicator variable for the post-crisis period and rating actions.

Table 4 presents the results for the two specifications. Consistent with the intuition from the literature on credit rating agencies (deHaan 2017), S&P's rating actions are more useful for fraud prediction after the financial crisis. First, Panel A shows that the increase in the AUC after including S&P's rating actions in the fraud prediction model is larger

[17] Untabulated analyses show that when we regress *F-score* on these firm characteristics, we obtain an adjusted R^2 of 73 percent. The correlation coefficients between *F-score* and these variables show that *F-score* is significantly correlated with all of them at the 1 percent level, with coefficients as high as 0.79 for *TANG* (tangible assets).

TABLE 4

Predictability of Rating Actions for Accounting Fraud—Pre- and Post-Financial Crisis

Panel A: Predictability of Rating Actions for Accounting Fraud—Pre- and Post- Financial Crisis Using Subsample Regressions

Dep. Var. =	***Prob (Fraud = 1)***							
	Pre-Crisis				**Post-Crisis**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
F-score	0.479***	0.482***	0.481***	0.483***	0.824*	0.829*	0.824*	0.826*
	(2.79)	(2.81)	(2.81)	(2.82)	(1.87)	(1.88)	(1.88)	(1.88)
Action_SP		0.193		0.154		**0.845*****		**0.875*****
		(1.15)		(0.95)		**(2.63)**		**(2.98)**
Action_EJR			0.181	0.144			0.032	−0.133
			(1.52)	(1.36)			(0.12)	(−0.60)
ABSI	8.071***	7.980***	8.014***	7.953***	−1.189	−1.634	−1.203	−1.587
	(3.82)	(3.76)	(3.80)	(3.76)	(−0.34)	(−0.47)	(−0.34)	(−0.46)
RET	−0.622	−0.583	−0.574	−0.552	−1.835***	−1.631***	−1.826***	−1.661***
	(−1.57)	(−1.57)	(−1.53)	(−1.53)	(−3.13)	(−2.73)	(−3.00)	(−2.70)
Prior_RET	−0.018	0.004	−0.002	0.012	−0.737	−0.628	−0.733	−0.643
	(−0.11)	(0.02)	(−0.01)	(0.08)	(−0.96)	(−0.85)	(−0.96)	(−0.87)
ΔREC	−0.476***	−0.473***	−0.468***	−0.467***	−0.342	−0.305	−0.340	−0.308
	(−3.41)	(−3.45)	(−3.44)	(−3.47)	(−0.59)	(−0.55)	(−0.59)	(−0.56)
ΔCDS	0.712	0.533	0.536	0.435	6.454	6.235	6.439	6.412
	(0.31)	(0.26)	(0.26)	(0.23)	(0.72)	(0.82)	(0.72)	(0.82)
AUC	0.626	0.629	0.627	0.629	0.650	0.664	0.650	0.665
Incremental AUC		(2) versus (1)	(3) versus (1)	(4) versus (1)		(6) versus (5)	(7) versus (5)	(8) versus (5)
(Chi-square)		***0.003****	*0.001*	***0.003*****		***0.014*****	*0.000*	***0.015*****
		(3.74)	*(1.09)*	***(4.28)***		***(6.00)***	*(0.05)*	***(6.44)***
				(4) versus (2)				(8) versus (6)
				0.000				*0.001*
				(0.50)				*(0.39)*
				(4) versus (3)				(8) versus (7)
				0.002*				***0.015*****
				(3.57)				***(6.43)***
# of fraud-quarters	1,298	1,298	1,298	1,298	299	299	299	299
# of nonfraud quarters	22,821	22,821	22,821	22,821	21,597	21,597	21,597	21,597

(continued on next page)

TABLE 4 (continued)

Panel B: Fraud Prediction Performance Pre- and Post-Financial Crisis—Fraud Score Cutoff set at 1

	Pre-Crisis Period						**Post-Crisis Period**					
	F-score			***F-score* and *Action_SP***			***F-score***			***F-score* and *Action_SP***		
Observed	**Fraud**	**Nonfraud**	**Total**	**Fraud**	**Nonfraud**	**Total**	**Fraud**	**Nonfraud**	**Total**	**Fraud**	**Nonfraud**	**Total**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Fraud firm-quarters	809	489	1,298	811	487	1,298	199	100	299	210	89	299
Nonfraud firm-quarters	10,690	12,131	22,821	10,530	12,291	22,821	10,744	10,853	21,597	9,712	11,885	21,597
Total	11,499	12,620	24,119	11,341	12,778	24,119	10,943	10,953	21,896	9,922	11,974	21,896
Fraud firm-quarters (%)	62.33	37.67	5.38	62.48	37.52	5.38	66.56	33.44	1.37	70.23	29.77	1.37
Nonfraud firm-quarters (%)	46.84	53.16	94.62	46.14	53.86	94.62	49.75	50.25	98.63	44.97	55.03	98.63
Correct classification (%)		53.65			54.32			50.47			55.24	
Sensitivity (%)		62.33			62.48			66.56			70.23	
Type I errors (%)		46.84			46.14			49.75			44.97	
Type II errors (%)		37.67			37.52			33.44			29.77	

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TABLE 4 (continued)

Panel C: Predictability of Rating Actions for Accounting Fraud—Pre- and Post-Financial Crisis Using Pooled Regressions

Dep. Var. =	***Prob (Fraud = 1)***	
	(1)	**(2)**
Action_SP * Post	**0.716****	**0.721****
	(2.07)	**(2.17)**
Action_EJR * Post	−0.258	−0.277
	(−0.92)	(−1.15)
*F-score * Post*		0.343
		(0.77)
*ABSI * Post*		−9.540**
		(−2.40)
*RET * Post*		−1.108
		(−1.60)
*Prior_RET * Post*		−0.654
		(−0.88)
*ΔREC * Post*		0.159
		(0.29)
*ΔCDS * Post*		5.977
		(0.73)
Post	−1.426***	0.517
	(−4.59)	(0.20)
F-score	0.551***	0.483***
	(3.15)	(2.83)
Action_SP	0.158	0.154
	(0.98)	(0.97)
Action_EJR	0.136	0.144
	(1.24)	(1.39)
ABSI	5.852***	7.953***
	(2.97)	(3.80)
RET	−0.661**	−0.552
	(−2.03)	(−1.57)
Prior_RET	−0.051	0.012
	(−0.32)	(0.08)
ΔREC	−0.470***	−0.467***
	(−3.67)	(−3.55)
ΔCDS	0.974	0.435
	(0.43)	(0.24)
# of fraud-quarters	1,597	1,597
# of nonfraud-quarters	44,418	44,418

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table presents the usefulness of credit rating actions for predicting accounting fraud before and after the 2008–2009 financial crisis, that is, for firm-quarter ends before or after June 30, 2009 (see NBER 2023). Panel A presents the regression results separately for the pre- and post-crisis periods. Panel B compares the fraud prediction performance (defined in Table 2) between models with only *F-score* components and those with both *F-score* components and rating actions for the two subperiods. Panel C presents pooled regressions. Standard errors are clustered by firm and year.
Variable definitions are presented in the Appendix A.

in the post-crisis period (1.4 percent, significant at the 5 percent level) than in the pre-crisis period (0.3 percent, significant at the 10 percent level). Second, correct classification and sensitivity improve more and type I and type II errors decrease more after the crisis due to adding S&P's rating actions to the fraud prediction model (Table 4, Panel B). Specifically, after the crisis, adding S&P's rating actions to the *F-score*-only model improves correct classification and sensitivity by 4.77 and 3.67 percent, respectively, and reduces type I and II errors by 4.78 and 3.67 percent, respectively. In contrast, before the crisis, adding S&P's rating actions to the *F-score*-only model improves the correct classification rate and reduces type I errors by about 0.7 percent each, and it improves sensitivity and reduces type II errors each by 0.2 percent. Third, the interactions between S&P's rating actions and the indicator for post-crisis period in the pooled model is significant at the 5 percent level (Table 4, Panel C). In contrast, we find no difference in the predictability of EJR's rating actions for accounting fraud, likely because investor-paid CRAs were not under increased pressure to issue more timely and informative ratings after the financial crisis.

Overall, our analyses offer consistent and robust evidence that rating actions from issuer-paid CRAs provide useful information, beyond fraud indicators based on financial statements and other capital market participants, in accounting fraud prediction. This evidence, combined with the insignificant results of investor-paid CRAs' rating actions, suggests that investor-paid CRAs' reliance on public information limits the incremental informativeness of their rating actions in predicting undisclosed fraud.

V. WHEN DO CRAS TAKE RATINGS ACTIONS AGAINST FRAUD FIRMS?

In this section, we assess when CRAs' rating actions are most informative in fraud prediction and compare the timeliness of the two CRAs in taking rating actions against fraud firms. The results provide additional evidence on the source of credit rating agencies' fraud-related information. Specifically, we conduct three sets of analyses. First, we examine whether the predictive ability of rating actions differs between different stages of fraud. Second, we use a fraud-firm-only sample to compare the two CRAs' rating actions in each quarter before fraud revelation. Third, we conduct a fraud-level analysis and investigate the earliest rating action that each CRA takes against fraud firms.

Usefulness of Rating Actions for Accounting Fraud Prediction in Different Fraud Stages

First, we classify fraud stages based on relative time periods by partitioning fraud firm-quarters into three groups: early (first third), middle (second third), and late (last third) fraud periods. We re-estimate the fraud prediction model in Equation (1) using only one of the three groups as fraud observations while keeping the nonfraud observations constant. We present the results in Table 5, Panel A.[18] Both coefficient estimates of CRAs' rating actions and the comparison of AUCs show that of the three subperiods, CRAs' rating actions are incrementally informative in predicting late-stage fraud (i.e., the last third of the fraud period) but largely not useful in identifying early- and middle-stage fraud beyond other signals (except for the significant coefficient of S&P's rating actions in the middle period). Focusing on the results in late-stage fraud, the rating actions of S&P dominate those of EJR in improving the model's ability to discern fraud firms. Specifically, although both CRAs' rating actions are statistically significant, the comparison of AUCs shows that adding EJR's rating actions does not improve the models in column (11) versus (9) and column (12) versus (10), whereas including S&P's rating actions increases the AUC by 1.5 percent in column (10) versus (9).[19]

As fraud durations vary across firms, we investigate when CRAs' rating actions are informative about fraud based on an absolute measure of time periods. To do so, we re-estimate the prediction models every two quarters ahead of fraud revelation (i.e., quarters $[-2, -1]$, quarters $[-4, -3], \ldots$) and tabulate the results in Table 5, Panel B. Based on the average fraud duration of SCAC and AAER cases (11.5 and 16.3 quarters, respectively) and the results in Table 5, Panel A, we anticipate that CRAs' rating actions become incrementally informative about fraud during the four to five quarters before fraud revelation. We find results consistent with this prediction.

First, neither CRA's rating actions provide incremental information more than four quarters ahead of fraud revelation. Second, during the three to four quarters before fraud revelation, only S&P's rating actions predict fraud and improve AUC by 2.6 percent, whereas EJR's rating actions fail to do so, as shown in columns (5)–(8). Third, although both CRAs' rating actions are positively and significantly related to the last two quarters of fraud, only those of S&P

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[18] We require both CRAs to cover the fraud firms in each of the three subperiods to ensure that the difference in rating actions' predictive ability is not due to changes in sample composition. In untabulated analysis, we relax this requirement and find similar results.

[19] In an untabulated analysis, we test whether fraud indicators and CRAs' rating actions can distinguish different stages of frauds. We include only fraud firm-quarters in the sample and use, as a dependent variable, an indicator variable that equals 1 for late-stage fraud and 0 for early- and middle-stage frauds. We find that coefficients on both *F-score* and EJR's rating actions are insignificantly different from 0, whereas the coefficient on S&P's rating actions is significantly positive (at the 1 percent level). This evidence is consistent with the results in Table 5, Panel A showing that S&P's rating actions contain information on late-stage frauds.

TABLE 5

Timeliness of Rating Actions before Fraud Revelation

Panel A: Rating Actions during Subperiods before Fraud Revelation

Dep. Var. =	***Prob (Fraud = 1)***											
	First Tercile				**Second Tercile**				**Third Tercile**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
F-score	0.584***	0.586***	0.585***	0.586***	0.777***	0.779***	0.778***	0.780***	0.427**	0.433**	0.432**	0.436**
	(2.71)	(2.71)	(2.71)	(2.71)	(3.19)	(3.20)	(3.21)	(3.21)	(2.33)	(2.35)	(2.36)	(2.37)
Action_SP		0.266		0.257		**0.311***		0.301		**0.649****		**0.562****
		(0.82)		(0.89)		**(1.67)**		(1.38)		**(2.40)**		**(1.98)**
Action_EJR			0.090	0.036			0.104	0.037			**0.441*****	**0.306***
			(0.29)	(0.13)			(0.42)	(0.14)			**(2.77)**	**(1.84)**
Control for other signals	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.617	0.619	0.618	0.619	0.637	0.641	0.638	0.641	0.626	0.641	0.630	0.642
Incremental AUC (Chi-square)		(2) versus (1)	(3) versus (1)	(4) versus (1)		(6) versus (5)	(7) versus (5)	(8) versus (5)		(10) versus (9)	(11) versus (9)	(12) versus (9)
		0.002	*0.001*	*0.002*		*0.004*	*0.001*	*0.004*		***0.015*****	*0.004*	***0.016*****
		(0.52)	*(0.61)*	*(0.66)*		*(2.41)*	*(0.30)*	*(2.52)*		***(7.90)***	(1.06)	***(7.52)***
				(4) versus (2)				(8) versus (6)				(12) versus (10)
				0.000				*0.000*				*0.001*
				(0.32)				*(0.01)*				*(0.04)*
				(4) versus (3)				(8) versus (7)				(12) versus (11)
				0.001				*0.003*				***0.012*****
				(0.26)				*(1.98)*				*(7.00)*
# of fraud quarters	326	326	326	326	423	423	423	423	514	514	514	514
# of nonfraud quarters	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418

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TABLE 5 (continued)

Panel B: Rating Actions during Six Quarters before Fraud Revelation

Dep. Var. =	***Prob (Fraud = 1)***											
	Quarters [−6, −5]				**Quarters [−4, −3]**				**Quarters [−2, −1]**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
F-score	0.576**	0.575**	0.577**	0.576**	0.597***	0.605***	0.597***	0.603***	0.507**	0.518**	0.517**	0.524**
	(2.17)	(2.17)	(2.19)	(2.18)	(3.10)	(3.16)	(3.09)	(3.14)	(2.04)	(2.07)	(2.08)	(2.09)
Action_SP		−0.213		−0.266		**0.780*****		**0.828*****		**0.938*****		**0.804*****
		(−0.63)		(−0.84)		**(3.06)**		**(3.08)**		**(3.39)**		**(2.74)**
Action_EJR			0.142	0.191			0.014	−0.197			**0.663*****	**0.460*****
			(0.53)	(0.76)			(0.08)	(−1.05)			**(4.15)**	**(2.78)**
Control for other signals	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.621	0.621	0.623	0.622	0.613	0.639	0.613	0.639	0.640	0.665	0.646	0.665
Incremental AUC (Chi-square)		(2) versus (1)	(3) versus (1)	(4) versus (1)		(6) versus (5)	(7) versus (5)	(8) versus (5)		(10) versus (9)	(11) versus (9)	(12) versus (9)
		0.000	*0.002*	*0.001*		***0.026*****	*0.000*	***0.026*****		***0.025*****	*0.006*	***0.025*****
		(0.18)	*(0.10)*	*(0.00)*		***(7.95)***	*(0.09)*	***(7.30)***		***(7.73)***	*(0.93)*	***(7.08)***
				(4) versus (2)				(8) versus (6)				(12) versus (10)
				0.001				*0.000*				*0.000*
				(0.13)				*(0.02)*				*(0.00)*
				(4) versus (3)				(8) versus (7)				(12) versus (11)
				−0.001				***0.026*****				***0.019*****
				(0.08)				*(7.24)*				***(6.68)***
# of fraud quarters	260	260	260	260	275	275	275	275	279	279	279	279
# of nonfraud quarters	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418	44,418

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

This table presents the usefulness of credit rating actions in terms of their timeliness before fraud revelation. Panel A partitions the fraud period into three terciles and presents the predictability of rating actions for accounting fraud in each tercile. Panel B presents the timeliness of rating actions during the six quarters before the fraud revelation. Standard errors are clustered by firm and year.

Variable definitions are presented in the Appendix A.

can significantly improve the model's ability to separate fraud and nonfraud firm-quarters. Specifically, including S&P improves the AUC by 2.5 percent in column (10), whereas adding ERJ does not improve AUC when comparing column (11) with (9) and column (12) with (10).

Combined, the results in this section suggest that CRAs' rating actions are incrementally informative in predicting late-stage fraud, especially during the four quarters prior to fraud revelation. The outperformance of S&P over EJR in improving the model's ability to discern fraud firm-quarters, especially in earlier fraud periods (i.e., three and four quarters before fraud revelation), is consistent with the former's access to material nonpublic information, which can improve the information used in its rating actions with regard to accounting fraud.

Timeliness of Rating Actions within the Fraud Sample

The previous section's results suggest that rating actions, especially those of S&P, can help predict late-stage fraud. In this section, we directly compare the two CRAs' relative timeliness by examining their tendency to take rating actions against fraud firms in each quarter. We begin with a univariate analysis of rating actions against fraud firms. Table 6, Panel A presents the two CRAs' rating actions in the two years before and after the fraud revelation. We label the three-month period that begins in the fraud revelation month the "fraud revelation quarter" (i.e., quarter 0). The three-month period before quarter 0 is labeled quarter -1, and quarters -2 to -8 are defined in the same way. Note that there are fewer fraud events prior to quarter -4 because some frauds last less than two years.

Column (2) shows that fraud firms suffer a significant decrease in S&P's ratings at least four quarters before the fraud revelation. In terms of economic magnitude, fraud firms experience an average decrease in their S&P ratings of 0.10, 0.05, 0.19, and 0.24 notches from quarter -4 to -1, respectively. In contrast, column (5) shows that EJR's ratings for fraud firms only significantly decrease two quarters before fraud revelation (0.36 and 0.31 notches in quarters -2 and -1, respectively). Column (4) shows that cumulatively, 49 percent of fraud firms face negative rating actions by S&P before fraud revelation, and these rating actions occur more frequently between quarters -4 and -1 than between quarters -8 and -5 (29 and 20 percent, respectively), and the difference is significant at the 5 percent level. Column (7) shows that EJR downgrades 41 percent of fraud firms before fraud revelation. Overall, our univariate results are consistent with the evidence in Table 5, Panel B and suggest that both S&P and EJR take significant negative rating actions against fraud firms before fraud revelation, and S&P acts sooner than EJR.

Next, because CRAs can take negative rating actions due to deteriorating economic fundamentals or observing actions from market participants and other information intermediaries, we use a regression analysis that controls for nonfraud determinants of rating actions to ascertain that these actions reflect fraud-related information. Empirically, we estimate the following regression at the firm-quarter level for the rating actions of S&P and EJR separately:

$$RatingActions = \alpha + \sum_i \beta_i \cdot FraudPeriod_i + \delta \cdot Controls\_RatingActions + \varepsilon, \quad (2)$$

where *FraudPeriod* is an indicator variable representing the quarters after fraud starts but before it is revealed. The control period (pre-fraud period) is one year before the beginning of the fraud period. The dependent variables are *Action_SP* and *Action_EJR*.

In addition to the information already available in the market before the CRAs' rating actions, which we have discussed in previous sections, we include an indicator variable of whether a firm-quarter overlaps with a private SEC investigation period to shed light on the role of access to nonpublic information. We obtain all private SEC investigations that closed between January 1, 2000 and August 2, 2017 from Blackburne, Kepler, Quinn, and Taylor (2021). Furthermore, following the models of Alp (2013) and Baghai, Servaes, and Tamayo (2014), we control for firm characteristics at the end of a firm-quarter with the following variables: *INTCOV*, *PM*, *LEV*, *SIZE*, *DEBT/EBITDA*, *EARNVOL*, *CASH*, *TANG*, *CAPEX*, *Q*, *RETEARN*, *RETVOL*, and *BETA*. Last, we include industry (based on Fama-French 48 industries) and year fixed effects to control for industry characteristics and macroeconomic trends that may lead to rating actions.[20] To address the concern that nonlinear models with a large number of fixed effects suffer from the incidental parameters problem, which may bias the parameter estimates and standard errors (Greene 2004), we use a linear probability model (Masulis and Zhang 2019). We report the t-statistics based on standard errors clustered by firm and year.

Table 6, Panel B presents the regression results. Columns (1) and (2) show that when we control for economic fundamentals and publicly available information, S&P expresses its negative opinion on fraud firms' creditworthiness as early as four quarters before fraud revelation (significant at the 5 or 1 percent level), whereas EJR does not downgrade fraud

[20] As a robustness check, we separately control for industry or year fixed effects in Tables 6 and 7. All our inferences continue to hold (untabulated).

TABLE 6

Timeliness of Rating Actions before Fraud Revelation—Within-Fraud-Firm Analysis

Panel A: Univariate Analysis of Rating Actions against Fraud Firms

		S&P's Rating Actions			EJR's Rating Actions		
Quarter	# of Fraud Events	ΔRate_SP	Cumulative Number of Negative Actions	Cumulative Percentage of Negative Actions	ΔRate_EJR	Cumulative Number of Negative Actions	Cumulative Percentage of Negative Actions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
−8	110	−0.080**	10	9	−0.050	4	4
−7	127	0.000	15	12	−0.065*	11	9
−6	147	−0.036*	21	15	−0.053	22	15
−5	163	0.026	32	20	0.053	28	17
−4	**177**	−0.095**	**44**	**25**	−0.007	**34**	**19**
−3	**177**	−0.053**	**60**	**34**	−0.019	**42**	**24**
−2	**177**	−0.186***	**72**	**41**	−0.360***	**59**	**33**
−1	**177**	−0.244***	**86**	**49**	−0.311***	**73**	**41**
0	177	−1.000***	119	67	−1.211***	111	63
1	177	−0.430***	125	71	−0.379***	121	68
2	177	−0.375***	131	74	−0.485***	127	72
3	177	−0.187***	134	76	−0.067	130	73
4	177	−0.055	136	77	−0.074	135	76
5	177	−0.234***	137	77	0.043	138	78
6	177	−0.029	138	78	0.012	139	79
7	177	−0.036	142	80	−0.138	144	81

Panel B: Firm-Quarter Differences in the Timeliness of S&P's and EJR's Rating Actions

Dep. Var. =	*Action_SP*	*Action_EJR*	*Differences*
	(1)	(2)	(1) versus (2)
Qtr_[9,12]	−0.015	−0.030	−0.015
	(−1.36)	(−1.31)	(0.34)
Qtr_8	0.011	−0.059*	0.070
	(0.45)	(−1.80)	(2.39)
Qtr_7	−0.017	−0.012	−0.005
	(−0.66)	(−0.29)	(0.03)
Qtr_6	−0.021	0.003	−0.024
	(−0.95)	(0.12)	(0.42)
Qtr_5	−0.028	−0.033	0.050
	(−1.53)	(−0.92)	(0.03)
Qtr_4	**0.064****	−0.030	***0.094*****
	(1.98)	(−0.84)	***(5.51)***
Qtr_3	**0.069****	−0.024	***0.093*****
	(2.43)	(−0.83)	***(6.33)***
Qtr_2	**0.095*****	**0.067***	0.028
	(2.74)	**(1.74)**	(0.45)
Qtr_1	**0.128*****	0.054	***0.074****
	(2.62)	(1.38)	***(3.06)***
Qtr_0	0.301***	0.295***	
	(6.64)	(6.76)	

(continued on next page)

TABLE 6 (continued)

Dep. Var. =	***Action_SP***	***Action_EJR***	***Differences***
	(1)	**(2)**	**(1) versus (2)**
F-score	−0.027	−0.019	
	(−1.11)	(−0.59)	
ABSI	0.163**	0.253*	
	(2.42)	(1.67)	
RET	−0.056	−0.191***	
	(−1.50)	(−5.46)	
Prior_RET	−0.041***	−0.034**	
	(−3.02)	(−2.18)	
ΔREC	−0.113***	−0.060*	
	(−2.69)	(−1.66)	
ΔCDS	1.255	2.349***	
	(0.95)	(4.74)	
SEC	0.049**	0.039	
	(2.01)	(1.44)	
INTCOV	0.000	−0.001	
	(0.05)	(−1.44)	
PM	−0.089	−0.191***	
	(−1.00)	(−3.31)	
LEV	0.083	0.112	
	(1.19)	(1.37)	
SIZE	0.023***	0.028***	
	(3.73)	(5.93)	
DEDT/EBITDA	0.000	0.000	
	(0.98)	(0.26)	
EARNVOL	−0.036	−0.032	
	(−0.64)	(−0.48)	
CASH	−0.081	−0.040	
	(−0.61)	(−0.28)	
TANG	0.117*	−0.009	
	(1.65)	(−0.10)	
CAPEX	−0.383*	0.725**	
	(−1.94)	(2.00)	
Q	−0.001	−0.011	
	(−0.21)	(−1.03)	
RETEARN	0.033	0.015	
	(1.17)	(0.31)	
RETVOL	3.744***	1.040	
	(3.95)	(1.08)	
BETA	−0.015	−0.018	
	(−1.20)	(−0.93)	
Year FE	Yes	Yes	
Industry FE	Yes	Yes	
# of Firm-quarters	2,218	1,825	
Adjusted R^2	0.19	0.20	

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table presents quarterly S&P's and EJR's rating actions before fraud revelation. Panel A presents the univariate data of quarterly rating changes. Panel B presents the results from the regression analyses. In Panel B, the sample period begins four quarters before the fraud starts and ends in the month in which it is publicly revealed. All regressions are estimated using a linear probability model and control for industry (Fama-French 48 industries) and year fixed effects. Standard errors are clustered by firm and year.
Variable definitions are presented in the Appendix A.

firms until two quarters before fraud revelation (significant at the 10 percent level in quarter −2). F-tests show the differences in quarters −4, −3, and −1 between S&P and EJR are significant (at the 5, 5, and 10 percent levels, respectively), consistent with the results in Table 5, Panel B and Table 6, Panel A. Relative to the pre-fraud period, S&P is 6.4, 6.9, 9.5, and 12.8 percent more likely to take negative rating actions against fraud firms in the four quarters before the public revelation of the fraud (corresponding, respectively, to 19, 20, 28, and 38 percent of the within-fraud-firm Std. Dev. of the quarterly S&P's negative rating actions of 0.337), whereas EJR is 6.7 percent more likely to take negative rating actions two quarters before the public revelation of the fraud (corresponding to 19 percent of the within-fraud-firm Std. Dev. of the quarterly EJR's rating downgrades of 0.350).

The coefficients of the control variables are generally consistent with our expectations. For example, firms with lower stock returns and higher short interest are more likely to face negative rating actions. *SEC* is significantly and positively associated with S&P's negative rating actions against the fraud firms but not with those of EJR. As information about private SEC investigations is more likely to be accessible to S&P but not to EJR, this result suggests that access to private information may play a role in issuer-paid CRAs' rating actions against fraud firms.

CRAs' Earliest Rating Actions against Fraud Firms

In the last set of analyses on CRAs' timeliness, we use a fraud-CRA level research design to compare the timing of CRAs' earliest rating actions against fraud firms. This design can quantify the differences in timeliness between the two CRAs' rating actions and supplement the quarterly-level analyses of the previous section.

We first identify fraud firms subject to negative rating actions by either S&P or EJR before fraud revelation. Based on the results from the previous two sections, we focus on the 89 (105) frauds that receive negative rating actions during the one year (two years) before fraud revelation, as these rating actions are more likely to be associated with fraud than earlier ones. Each fraud has two observations, one for S&P and one for EJR. We define a CRA's *TIMELINESS* as the interval between its earliest rating action and the fraud revelation date scaled by the length of the period (one or two years). We set *TIMELINESS* to 0 if a CRA does not take any negative rating action during the period. Higher values of *TIMELINESS* indicate more timely rating actions. Untabulated summary statistics of *TIMELINESS* show that S&P's rating actions are on average more timely than those of EJR in the context of fraud firms. Specifically, the mean and median values of *TIMELINESS* for S&P within one year (two years) before fraud revelation are 0.57 and 0.50 (0.45 and 0.35), respectively, corresponding to 208 and 183 days (329 and 256 days) before fraud revelation; the mean and median values of *TIMELINESS* for EJR are 0.35 and 0.35 (0.29 and 0.16), corresponding to 128 and 128 days (212 and 117 days) before fraud revelation.

Next, we use a regression approach to control for nonfraud determinants of rating actions. Specifically, we regress *TIMELINESS* on the variable of interest, *S&P*, an indicator variable that equals 1 for S&P observations and 0 for EJR observations. We use the same set of controls as in Table 6 but measure them using the mean of these variables during the period (one or two years). Table 7 shows that S&P takes rating actions much earlier than EJR (the coefficients of *S&P* are significant at the 5 and 1 percent levels in the one- and two-year samples, respectively), consistent with the patterns documented in Tables 5 and 6. In terms of economic magnitude, the coefficients in columns (1) and (2) suggest that, on average, S&P's earliest rating action is 83 days (0.227 × 365) and 121 days (0.166 × 730) ahead of that of EJR, respectively.

TABLE 7

Timeliness of Rating Actions before Fraud Revelation—Fraud-Level Analysis

Dep. Var. =	**Timeliness**	
	One Year before Fraud Revelation	**Two Years before Fraud Revelation**
	(1)	**(2)**
S&P	**0.227****	**0.166*****
	(1.97)	**(2.94)**
F-score	−0.074	−0.034
	(−0.19)	(−0.16)

(continued on next page)

TABLE 7 (continued)

Dep. Var. =	Timeliness	
	One Year before Fraud Revelation (1)	Two Years before Fraud Revelation (2)
ABSI	2.500	1.510**
	(1.49)	(2.07)
RET	0.308	0.219*
	(1.11)	(1.86)
Prior_RET	0.082	−0.144
	(0.32)	(−1.51)
Δ*REC*	−0.178	−0.097
	(−0.69)	(−0.97)
Δ*CDS*	−0.743	−0.013
	(−0.17)	(−0.01)
SEC	0.313	0.205**
	(1.42)	(2.20)
INTCOV	−0.005	−0.003
	(−0.95)	(−0.86)
PM	0.199	0.263
	(0.71)	(0.99)
LEV	−0.316	−0.382
	(−0.52)	(−1.22)
SIZE	0.010	0.031
	(0.12)	(0.75)
DEDT/EBITDA	0.001	0.003
	(0.29)	(0.52)
EARNVOL	0.625	0.369
	(0.99)	(1.27)
CASH	−2.111	−1.027
	(−1.29)	(−1.35)
TANG	−0.662	0.028
	(−0.60)	(0.05)
CAPEX	−1.080	−2.659*
	(−0.33)	(−1.76)
Q	0.077	0.002
	(0.49)	(0.03)
RETEARN	−0.122	0.038
	(−0.73)	(0.23)
RETVOL	−8.802	−4.184
	(−0.92)	(−0.77)
BETA	0.142	0.265**
	(0.44)	(2.03)
Year FE	Yes	Yes
Industry FE	Yes	Yes
# of obs.	178	210
Adjusted R^2	0.37	0.45

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table compares the timeliness of S&P's and EJR's earliest rating actions in the one year or two years prior to fraud revelation.
Variables are defined as the average of the firm-year in the sample following the Appendix A.

In sum, our analyses provide robust and consistent evidence that for fraud prediction, S&P's rating actions are more timely, and therefore more useful, than those of EJR. On average, issuer-paid CRAs downgrade fraud firms or place them on negative credit watch as early as four quarters before fraud revelation, whereas investor-paid CRAs do not adjust their ratings until two quarters before fraud revelation. In terms of the timing of the first negative rating actions, S&P acts roughly three to four months earlier than EJR.

VI. CONCLUSION

This study examines whether and when credit rating actions are useful for fraud prediction. We construct a sample of 177 accounting frauds from 1999 to 2018 covered by both S&P (an issuer-paid CRA) and EJR (an investor-paid CRA) based on settled securities class action lawsuits against firms engaging in accounting misstatements and AAERs. Using this sample, we find that the rating actions of S&P can predict accounting fraud, incremental to the predictive power of *F-score* and other market participants. In contrast, the predictive ability of EJR's rating actions is muted by other market participants, consistent with EJR's reliance on public information sources. Furthermore, S&P's rating actions are useful for fraud prediction as early as four quarters before fraud revelation. EJR, which lacks access to management and material nonpublic information, can do so only two quarters ahead of fraud revelation.

Overall, our findings support the conjecture that issuer-paid CRAs' rating actions are useful for predicting fraud among the firms they cover. We show that although CRAs may not explicitly acknowledge fraud detection as part of their mission, their rating actions nonetheless can contribute to fraud detection in a meaningful and significant manner.

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APPENDIX A

Variable Descriptions

Variables	Definition
Fraud	An indicator variable that equals 1 for firm-quarters after fraud starts but before it is revealed, and 0 otherwise.
Action_SP	An indicator variable that equals 1 if a firm-quarter receives a rating downgrade or is placed on negative credit watch by S&P, and 0 otherwise.
Action_EJR	An indicator variable that equals 1 if a firm-quarter receives a rating downgrade by EJR, and 0 otherwise.
Downgrade_SP	An indicator variable that equals 1 if a firm-quarter receives a rating downgrade by S&P, and 0 otherwise.
F-score	Firm-quarter *F-score* based on the quarterly values of Model 2 components and the corresponding coefficient estimates in Dechow et al. (2011).
F-score (Model3)	Firm-quarter *F-score* based on the quarterly values of Model 3 components and the corresponding coefficient estimates in Dechow et al. (2011).
KS	Firm-quarter *ex ante* litigation risk based on the quarterly values of Model 3 components and the corresponding coefficient estimates in Kim and Skinner (2012, 302).
M-score	Firm-quarter *M-score* based on the quarterly values of components and the corresponding coefficient estimates in Beneish (1999).
RET	A firm-quarter's market-adjusted buy-and-hold return. If a firm-quarter experiences any rating actions, *RET* is calculated for a 91-day window that ends two days before the earliest rating action.
Prior_RET	The market-adjusted buy-and-hold return during the one year before the window used to calculate *RET*.
ABSI	A firm-quarter's average monthly abnormal short interest, estimated monthly by regressing monthly normal short interest on the monthly tercile rank of market value, book-to-market ratio, stock-return momentum, and industry indicators (Karpoff and Lou 2010). Normal short interest is defined as short interest scaled by the number of shares outstanding at the end of each month. If a firm-quarter experiences any rating actions, *ABSI* is calculated for the 91-day window that ends two days before the earliest rating action.

(continued on next page)

APPENDIX A (continued)

Variables	Definition
ΔREC	The changes in analysts' recommendations during the current quarter. If a firm-quarter experiences any rating actions, it represents the changes in analyst recommendations during the 91-day window that ends two days before the earliest rating action.
ΔCDS	The changes in five-year CDS spreads during the current quarter. If a firm-quarter experiences any rating actions, it represents the changes in five-year CDS spreads during the 91-day window that ends two days before the earliest rating action.
Post	An indicator variable that equals 1 if a firm-quarter ends after June 30, 2009 (see NBER 2023), and 0 otherwise.
INTCOV	The ratio of EBITDA to interest expense of the current quarter.
PM	The ratio of EBITDA to revenue of the current quarter.
LEV	The sum of long-term and short-term debt divided by total assets at the end of the current quarter.
SIZE	The logarithm of total assets (in millions of U.S. dollars) at the end of the current quarter.
DEBT/EBITDA	The ratio of the sum of long-term and short-term debt to EBITDA at the end of the current quarter.
EARNVOL	The standard deviation of *PM* in the five years by the end of the current quarter.
CASH	The ratio of cash to total assets at the end of the current quarter.
TANG	The ratio of net property, plant, and equipment to total assets at the end of the current quarter.
CAPEX	The ratio of capital expenditure to total assets of the current quarter.
Q	The ratio of the sum of total liabilities and market value of equity to total assets at the end of the current quarter.
RETEARN	The ratio of retained earnings to total assets at the end of the current quarter.
RETVOL	The standard deviation of the daily residual returns of the current quarter, adjusted for quarterly mean value of all rated firms. Daily residual returns are obtained by regressing daily stock returns on daily value-weighted market index returns.
BETA	The coefficient obtained by regressing daily stock returns on daily value-weighted market index returns for the current quarter, adjusted for quarterly mean value of all rated firms.
$\Delta Rate\_SP$	Changes in firm-quarter S&P's long-term issuer credit ratings.
$\Delta Rate\_EJR$	Changes in firm-quarter Egan-Jones long-term issuer credit ratings.
SEC	An indicator variable that equals 1 if a firm-quarter overlaps with a private SEC investigation, and 0 otherwise. We obtain data on private SEC investigations from Blackburne et al. (2021).
TIMELINESS	The number of days between the date of the earliest rating action and the fraud revelation date, scaled by 365 (730) for the one-year (two-year) horizon.
S&P	An indicator variable that equals 1 for observations based on rating actions taken by S&P, and 0 for observations based on rating actions taken by EJR.