Credit Rating Agencies and Accounting Fraud Detection

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Abstract

This study examines whether and when credit rating agencies (CRAs) take negative rating actions against issuers committing accounting fraud before the fraud is publicly revealed and the economic impact of such rating actions. Our findings show that these fraud firms experience a greater number of negative rating actions during the four quarters prior to the public fraud revelation, including lower ratings, more rating downgrades, and more negative credit watch additions, compared to firms with similar economic fundamentals and stock performance. Our findings also show that such negative rating actions are not limited to fraud firms in financial distress, suggesting that our effect reflects CRA responses to accounting fraud per se. In addition, we find CRAs take more timely actions when frauds are more severe, when they involve accounts more often scrutinized by CRAs during their credit analysis, and when short sellers target firms. Last, we find that CRAs' negative rating actions against fraud firms are informative to the market and are associated with shorter fraud duration. Overall, we conclude that CRAs possess private information about accounting fraud prior to the public revelation of this fraud and that they incorporate this information into negative ratings actions, accelerating fraud discovery.

Keywords: credit rating agency; accounting fraud; rating actions; securities class action lawsuits.

JEL classification: G24; K22; M41.

1. Introduction

Accounting fraud imposes severe costs on both firms and their stakeholders in the form of higher cost of capital, inefficient resource allocation, regulatory sanctions, and investment losses (Dechow et al. 1996; Hribar and Jenksins 2004; Graham et al. 2008; Karpoff et al. 2008; Cornil 2009; Kravet and Shevlin 2010). Even though shareholders usually suffer the brunt of these damages, debtholders can also be affected if firms miss contractual payments or declare bankruptcy as a result of financial deterioration. While credit rating agencies (hereafter CRAs) traditionally act as gatekeepers for public debtholders, their role and responsibility in detecting accounting fraud remains a question open to discussion.

On the one hand, CRAs are in a unique position to detect accounting fraud. First, they have access to non-public information (Bonsall 2014; Ahn et al. 2019). While Regulation Fair Disclosure (Reg FD) prevents the selective disclosure of information to other information intermediaries, CRAs are specifically exempt from this restriction (Jorion et al. 2005). Second, CRAs state clearly in their rating framework that a firm's financial transparency affects their rating decisions (Standard & Poor's 2017). Consistent with this claim, academic studies document that CRAs give higher ratings to firms with more conservative accounting methods (Ahmed et al. 2002), better accrual quality and earnings timeliness (Ashbaugh-Skaife et al. 2006), and more transparent accounting disclosures (Bonsall and Miller 2017). Similarly, Kraft (2015) finds that aggressive accounting and internal control weakness increase CRAs' perception of a firm's credit risk. Last, CRAs have reputational incentives to ensure that their ratings are accurate and thus should scrutinize firm financial reports (Cheng and Neamtiu 2009; de Haan 2017).

However, while CRAs are uniquely positioned to glean information about potential accounting fraud, they have been criticized by both investors and regulators for failing to sufficiently assess the quality of financial reporting, especially in the wake of the high-profile fraud cases of the early 2000s (SEC 2003; Frost 2007). Indeed, the more recent financial crisis has generated further debate on whether CRAs have the expertise to analyze complex transactions and products. Consistent with this view, Alissa et al. (2013) and Jung et al. (2013) find that debt issuers that manage earnings obtain higher credit ratings, suggesting that CRAs do not fully recognize accounting manipulation attempts. Furthermore, CRAs specifically define their role as one that "heavily relies on the quality, completeness and veracity of information" disclosed in firms' published financial statements, and not one focused on "searching for and exposing frauds."[1] Finally, it is possible that, even if CRAs detect accounting fraud, they may withhold a negative rating action due to incentives to cater to issuers (Becker and Milbourn 2011; Jiang et al. 2012; Griffin et al. 2013) or to stabilize ratings for contracting or regulatory concerns. (Beaver et al. 2006; Cheng and Neamtiu 2009).

To contribute insight into the role of CRAs in detecting fraud, we investigate whether and when CRAs take negative rating actions against firms that commit accounting fraud before the fraud is publicly revealed. We also explore the economic consequences of such rating actions. Specifically, we are interested in: 1) whether CRAs take negative rating actions against fraud firms before the fraud is publicly revealed, 2) whether CRAs' negative rating actions are at least partly driven by the accounting fraud per se, 3) the determinants of the timeliness of such rating actions, and 4) the consequences of such rating actions, including market reactions and fraud duration.

To conduct our analysis, we use the Securities Class Action Clearinghouse database (hereafter, SCAC) to obtain a sample of 259 securities class-action lawsuits that allege accounting misstatements where the defendant firms have received credit ratings from Standard & Poor's

[1] Quote from Moody's President Raymond McDaniel to the Securities and Exchange Commission (SEC) on November 21, 2002 (available at https://www.sec.gov/news/extra/credrate/moodys.htm).

(S&P). Of these firms, we find that 38% (30%) receive rating downgrades (negative credit watches) during the two years before fraud revelation. On average, they experience a cumulative downgrade of a 0.63 notch during the four quarters before the public fraud revelation, which equals 68% of the average downgrade magnitude during the quarter in which the fraud becomes public (a 0.92 notch).

To isolate rating actions due to fraud rather than firm performance or other risk factors that drive both credit risk and fraud propensity, we perform three sets of analyses. First, we run our analyses controlling for firm economic fundamentals as well as other sources of information, such as expected default frequency, stock returns, and abnormal short interest, and continue to find that fraud firms have lower ratings, greater likelihood of being downgraded or being issued a negative credit watch during the four quarters before fraud revelation.[2] Second, we use propensity score matching to match each fraud firm with a non-fraud firm from the same industry and with comparable economic fundamentals. In this analysis, we use three different windows in the matching procedures to ensure similarities between fraud and non-fraud firms, including economic performance in the year before the start of the fraud period, *changes* in economic fundamentals during the two years prior to the public fraud revelation, and a firm-quarter level match based on firm financials and stock returns in the last quarter to further control for economic fundamentals not yet captured by reported financial statements. Our results from our matching analysis reinforce our main findings. Third, we run our analyses controlling for firm financial distress. We find that CRAs take negative rating actions against not only fraud firms in distress, but also those that are financially healthy. Taken together, this set of analyses reinforces our conjecture that CRA negative rating actions are likely due to the detection of fraud in and of itself.

[2] In an untabulated analysis, we control for credit default swap (CDS) contracts and the issuance of new bank loans as alternative information sources. Our inferences continue to hold.

Next, to shed light on how CRAs detect frauds and incorporate this information into their ratings, we investigate the determinants of the timeliness of CRAs' rating actions against fraud firms. In this analysis, we find that CRAs take more timely actions when a fraud is more severe, when it involves misstatements in accounts routinely scrutinized by CRAs such as long-term tangible assets, intangible assets, and liabilities, and when fraud firms experience abnormally high short sales.

Last, we explore the consequences of CRAs' negative rating actions including the market reactions to rating actions as well as the duration of the fraud period. We find that downgrades of fraud and non-fraud firms elicit similar magnitudes of market reactions. Since our earlier results show that CRAs' downgrades of fraud firms are driven by both their deteriorating economic fundamentals as well as fraud while those of non-fraud firms are only due to deteriorating fundamentals, this finding suggests that the market perceives downgrades due to fraud as informative as those due to deteriorations in economic fundamentals. Moreover, we find that negative rating actions are associated with shorter fraud periods when we control for economic fundamentals and short selling (Karpoff and Lou 2010). Taken together, this set of analyses supports that CRAs' negative rating actions provide relevant information to the equity market and contribute to the public identification of firm fraud.

Our study contributes to two streams of literature. First, it sheds light on the question of whether credit ratings contain private information about issuers (Jorion et al. 2005; Ahn et al. 2019) by showing that CRAs incorporate this information into their ratings. In this way, they facilitate fraud discovery and play an essential information intermediary role in the capital market. Our findings also shed light on whether CRAs contribute to fraud detection by suggesting that, since

CRAs pay more attention to accounting items of greater relevance to long term default risk, they are more capable of detecting fraud involving these items.

Second, we contribute to the literature on the detection of accounting fraud. Within this area of research, Dyck et al. (2010) find that employees, the media, and industry regulators are the major whistle blowers in corporate fraud cases. In addition, other capital market participants, such as short sellers and transient institutional investors, are able to detect financial fraud (Desai et al. 2006; Hribar et al. 2009; Karpoff and Lou 2010). Regarding negative actions against fraud firms, Chen (2016) finds that banks, an important debt market participant, charge higher interest rates and impose more demanding contract terms for firms that have committed accounting malpractice. Compared with Chen (2016), our study focuses on CRAs, which serve the public segment of the debt market and rely more on reputational incentives in detecting accounting frauds compared to banks who lend directly to borrowers and thus have private relationships with and greater economic exposure to borrowers. In addition, we perform a battery of empirical tests to address the endogeneity issue and show evidence that the rating actions are due to accounting fraud per se rather than any contemporaneous deterioration in the fraud firms' underlying economic fundamentals. Thus, our study complements Chen (2016) and shows that various financial intermediaries in the debt market can play a governance role in corporate financial reporting.

2. Prior Literature and Motivation

In this section, we review related prior literature and motivate our study. We first discuss the governance role of CRAs in corporate financial reporting. We then explore the role of other capital market participants in fraud detection.

2.1 The governance role of CRAs in corporate financial reporting

Although prior literature has highlighted the important intermediary role of CRAs in efficiently aggregating and disseminating information in the capital market (Wakeman 1984; Millon and Thakor 1985), their specific role in evaluating accounting quality remains an open question. In determining credit ratings, CRAs are clearly interested in financial statement quality. For example, the S&P (2017) identifies financial transparency as one of four major corporate governance characteristics that it uses in determining credit ratings. In the literature, Ahmed et al. (2002) and Ashbaugh-Skaife et al. (2006) find that CRAs give higher ratings to firms with more conservative financial reports as well as those with higher accrual quality and more timely earnings. In a similar vein, Kraft (2015) shows that Moody's incorporates both quantitative and qualitative information in its credit assessments, taking into account factors such as aggressive accounting practices and internal control deficiencies. Moreover, CRAs have access to non-public information through their Reg FD exempt status and are thus able to obtain information on firm credit agreements, acquisition agreements, private placement memoranda, and business projections and forecasts. This access to private information places CRAs in a position to detect suspicious accounting practices that are not yet publicly revealed. Indeed, prior research finds that CRAs have faster access to bad news that is not yet public than do other market participants (Ahn et al. 2019).

To gain greater insight into the role of CRAs in corporate governance, we interviewed the head of one of the top three rating agencies in the Asia-Pacific region who confirmed anecdotally that CRAs have better information access compared to other information intermediaries and that they have incentives to incorporate fraud information in their ratings. Concerning information access, the CRAs' privileged access to private information, as well as the use of non-disclosure agreements, allows them to directly observe proprietary information not available to other information intermediaries. For example, while equity analysts generate their own estimates for their earnings forecasting models, issuers usually provide rating analysts with three to five years' earnings and cash flow forecasts. Moreover, CRAs conduct regular site visits during the initial rating and again during each annual review. Site visits have been increasingly relied upon by investors and other market participants as a means of collecting private information (Jackson 2009; Muddy Water 2010; Brown et al. 2015; Cheng et al. 2016, 2019). During these site visits, rating analysts tour a firm's operations and also often have face-to-face talks with top executives, including CEOs and CFOs. Such private meetings are less rehearsed compared to public disclosure (Bushee et al. 2017; Park and Soltes 2018) which allows analysts to better gauge executives' management philosophy, personality, and integrity. Furthermore, this face-to-face setting allows analysts the chance to observe managers' vocal cues and facial expressions, which previous research has shown are useful in assessing a firm's future prospects (Mayew and Venkatachalam 2012, Blankespoor et al. 2017). These conversations with firm leaders provide ratings analysts with a distinct information advantage over investors and equity analysts who likely meet with only the firm's investor relations team during site visits (Brown et al. 2015). Regarding the incentive to incorporate fraud information into ratings, our interviews confirmed that CRAs are concerned with accounting quality, as fraud increases a firm's bankruptcy risk. As such, CRAs will request additional information if they are concerned about any reported accounting numbers.

While there are numerous reasons why CRAs would play a role in the detection of accounting fraud, a number of studies question both their tendency and their ability to do so. In relation to the high-profile accounting frauds in the early 2000s, CRAs were criticized for not having sufficiently considered reporting quality in their credit ratings (SEC 2003; Partnoy 2006; Frost 2007). The recent financial crisis has ignited further debate on whether CRAs possess sufficient expertise to analyze complex transactions and products (Coval et al. 2009). CRAs claim that they do not define their role as being active fraud detectors, and that they depend largely on the information provided to them.

Even if CRAs were to proactively search for and recognize fraud, it is unclear if they would incorporate this knowledge in their subsequent ratings given their relationships with firms. Most CRAs charge issuers an origination fee and periodic monitoring fees. They also offer related consulting services, such as pre-rating assessments, to issuers (Bolton et al. 2012). This incentive may compel CRAs to provide unduly favorable ratings (Griffin et al. 2013), especially for issuers from whom they obtain substantial revenues (He et al. 2012). Indeed, Beaver et al. (2006) and Cornaggia and Cornaggia (2013) document that issuer-paid CRAs (S&P and Moody's) are slower to identify default risk in their ratings of a firm than are investor-paid CRAs (Egan Jones and Rapid). From this perspective, even if CRAs are able to detect accounting fraud, they may not incorporate this knowledge into their ratings.

Consistent with this view, Alissa et al. (2013) and Jung et al. (2013) find that firms can retain favorable ratings or achieve rating upgrades by smoothing earnings and upward accruals and by real earnings management. In other studies, Lee (2012) and Zhang (2019) find that CRAs may not detect issuers' manipulations of their cash flow classifications. Finally, Liu et al. (2018) find that issuers who receive a negative credit watch can reduce their likelihood of being downgraded by manipulating their accruals.

Even if CRAs detect and act on fraud, we are interested in the question of whether they do so more efficiently or faster than other market participants. Prior research finds that rating agencies provide information to the market that financial analysts do not (Ederington and Goh 1998) and that post-Reg FD credit ratings provide greater informational value than those prior to Reg FD (Jorion et al. 2005). Nonetheless, it is possible that rating analysts do not have an advantage over other market participants. That is, sophisticated investors, such as institutional investors and short sellers, may still possess more expertise, financial incentives, and resources to detect fraud than do CRAs (Karpoff and Lou 2010).

2.2 Other capital market participants' role in accounting fraud detection

Our study lends insight into the research on whether capital market participants can identify financial reporting fraud. Within this stream of research, Desai et al. (2006) find that short sellers successfully target restating firms prior to the restatements and that they appear to use the level of accruals in making their trading decisions. Karpoff and Lou (2010) document that short sellers can anticipate financial misconduct as early as 19 months before the public revelation of fraud and that short sales are associated with timelier fraud exposures. Miller (2006) finds that 29% of press-published articles identify fraud prior to its public acknowledgment by either the firm or the SEC, highlighting the dual role of the press in identifying and publicizing instances of fraud. Hribar et al. (2009) find that transient institutional investors (those with shorter investment horizons and higher portfolio turnover) reduce their investment in restating firms in the quarter prior to the restatements while Griffin (2003) finds that equity analysts do not incorporate fraud in their forecasts prior to its public revelation. Finally, Chen (2016) finds that, during periods of misreporting by a borrower, banks adjust loan contract terms by charging higher interest rates, imposing more restrictive covenants, and demanding more collateral, relative to the borrower's past loan terms.

3. Sample Selection and Descriptive Data

To construct our sample, we obtain information on securities class action lawsuits from the SCAC. In a securities class action lawsuit, plaintiffs allege that managers have inflated a firm's stock price through the misrepresentation of fundamentals. We use these lawsuits instead of information regarding firm financial misconduct from other databases, such as the restatement databases from the Government Accountability Office, Audit Analytics, or the SEC's Accounting and Auditing Enforcement Releases, for two reasons. First, unlike accounting restatements which include both intentional and unintentional accounting irregularities, securities class action lawsuits require less subjective judgements of whether an event involves accounting fraud. Using securities class action lawsuits mitigates any issues related to classification errors and thus increases the power of our empirical tests (Amiram et al. 2018). Second, the SCAC data allows us to more accurately identify the initial fraud revelation dates (Karpoff et al. 2017). Since our primary objective is to examine whether and when CRAs take negative rating actions before the public revelation of fraud, it is critical to identify the initial revelation date as precisely as possible.

Panel A of Table 1 presents our data selection procedures. From the SCAC database, we first obtain information on securities class action lawsuits with class period end dates between 1996 and 2016 (the sample coverage of the SCAC starts in 1996, and our credit rating data end in 2017). Following Amiram et al. (2018), we restrict our sample to cases with allegations brought under Section 10(b) of the 1934 Securities Exchange Act (manipulative and deceptive devices) because these cases are most likely related to accounting frauds. We further require sample firms to be covered Compustat so that we can obtain their financials and S&P ratings. These requirements yield an initial sample of 3,360 class-action lawsuits. For each case, in addition to the class period start and end dates and the filing date, we obtain its specific allegations, final status (dismissed, settled, or ongoing), and settlement amount if there is any.

From this initial sample, we remove 2,210 cases without any S&P ratings during the class period and 238 cases that involve financial firms or firms without industry membership information (i.e., a two-digit NAICS of 52 and 99, respectively). We also exclude 446 cases where the class period length is less than one year because CRAs usually review financial statements annually and are thus less likely to detect frauds with such short durations.[3] Next, we exclude cases that allege only false forward-looking statements (142 cases) or non-accounting related malpractice (65 cases) since our focus is on allegations of misstatements related to GAAP violations (Amiram et al. 2018).[4] Our final sample includes 259 cases involving misstatements of accounting numbers in financial statements. Of these cases, 155 are settled, 91 are dismissed, and 13 remain ongoing as of January 2019.[5]

We use the class period end date as the initial fraud revelation date because it is usually the date that a corrective disclosure is made and the market knows the extent of the fraud (Booth 2012).[6, 7] Note that a corrective disclosure does not have to be made by the firm itself and can be made by information intermediaries such as analysts and journalists (Hoffner and Halavais 2006).

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3 In a sensitivity test, we repeat the main tests for these 446 cases, and do not observe CRAs taking negative rating actions before the fraud revelation.

4 Specifically, for each of the remaining 466 cases, two of the study's authors independently read through the detailed case description from the SCAC website and related allegation complaint reports to determine if the case involves misstatement of accounting numbers in financial statements (and, if so, which accounts), misleading forward-looking disclosures, or non-accounting related malpractice, such as bribery of the government, or allegations against equity analysts or underwriters. Differences in their classifications are then reconciled through discussion between the authors.

5 In a sensitivity test, we repeat our main analysis using only the settled cases because they are more likely to be related to frauds, i.e., excluding cases that were dismissed or ongoing, and find similar results.

6 Most securities class-action lawsuits use the "fraud-on-the-market" theory (*Basic Inc. v. Levinson*, 485 U.S. 224, 1988 and *Erica P. John Fund, Inc. v. Halliburton Co.*, 563 U.S. 804, 2011) and assume that, when frauds are revealed, the price incorporates that information and investors are no longer affected by the fraud.

7 An alternative is to use the lawsuit filing date, which is after the end of the class period. We do not use the filing date for two reasons. First, stocks usually have much more negative returns at the class period end date compared to the lawsuit filing date: the average (median) three-day market adjusted returned centered on the class period end dates and filing dates are -20.16% (-15.73%) and -4.51% (-1.07%), respectively. Thus, it is more likely that at least some fraud information is revealed at the end of class period. Second, although it is possible that frauds are not publicly revealed until after the end of the class period, using a later date will bias towards us finding CRAs taking rating actions before the fraud revelation.

Panel B of Table 1 presents the statistics for the duration and severity of fraud in our sample. We measure the duration of fraud as the number of quarters covered in the class action lawsuit's class period. From Panel B, we see that the average fraud duration is about two years (i.e., 8.26 quarters), comparable to that of the sample in Karpoff and Lou (2010). More importantly, the class period end dates for our sample lead the lawsuit filing dates by an average of 1.25 quarters, consistent with the lead dates obtained by Karpoff et al. (2017) for initial fraud revelation (i.e., roughly 1.2 quarters). This provides assurance that our class period end dates approximate the initial fraud revelation dates. Finally, the mean and median settlements are US$174 million and US$17 million, respectively, but can be as high as US$6.1 billion.

Panels C and D of Table 1 present the sample distribution by year and by industry, respectively. From Panel C, we see that the frequency of litigation peaks during the period 2002 to 2004, possibly reflecting the enactment of the Sarbanes-Oxley Act. From Panel D, we see that the manufacturing and information industries experience the greatest number of lawsuits, while the construction industry has the smallest number of lawsuits. The industry distribution for our sample firms is generally comparable with that of the universe of Compustat firms with S&P credit ratings during the same period.

Panel E of Table 1, which reports the frequency of misstated accounts for our sample, shows that most misstatements (56.37% of our sample) relate to revenue recognition. A revenue misstatement frequently involves an overstatement of accounts receivable (including an under-provision for doubtful accounts) (18.92%). Other frequently misstated accounts include operating expenses (31.66%), various liabilities, payables and reserve accounts (28.96%), long-term tangible assets and their impairment (19.31%), and inventory and cost of goods sold (15.06%).

Finally, Panel F of Table 1 provides a comparison of fraud firms' characteristics during the class period (i.e., fraud commitment period) and their characteristics one year prior to the beginning of the class period (i.e., pre-fraud period). Compared to the pre-fraud period, we find that fraud firms have higher expected default frequency (*EDF*), more negative stock returns (*RETURN*), a lower level of tangible assets (*TANG*), lower growth potential (*TOBINQ*), and higher return volatility (*RETVOL*) during the class period. They also suffer from lower ratings (*RATE*), a greater frequency of being downgraded (*DG*), and a greater probability of being put on a negative watch list (*NW*).

4. Negative Rating Actions Against Fraud Firms Prior to Public Revelation

4.1 Analyses of rating actions prior to fraud revelation

In our first set of analyses, we investigate whether CRAs take negative rating actions against fraud firms prior to the public revelation of fraud by examining the abnormal credit ratings of our sample firms during the 24-month prior to fraud revelation. We choose a 24-month window as Karpoff and Lou (2010) document that short sellers anticipate accounting fraud as early as 19 months before the fraud revelation. To the best of our knowledge, this is the earliest date that market participants are documented to have detected accounting fraud.

We use the S&P long-term issuer ratings from Compustat, which contains monthly firm ratings starting from 1985.[8] We convert the letter ratings into numerical values using an ordinal scale ranging from one for the lowest rated firms (C) to 20 for the highest rated firms (AAA).[9] To calculate abnormal ratings, we use the models in Alp (2013) and Baghai et al. (2014) to estimate expected credit ratings based on the following firm characteristics: interest coverage (*INTCOV*),

8 Prior studies show that S&P's and Moody's credit ratings are highly correlated (Bongaerts et al. 2012).
9 Since we have very few firms rated with C and CC, we assign the value one to both C and CC ratings.

profitability (*PM*), long-term debt leverage (*LTLEV*), total leverage (*LEV*), firm size (*SIZE*), debt-to-EBITDA (*DEBT/EBITDA*), an indicator for negative debt-to-EBITDA (*NEG_DEBT/EBITDA*), earnings volatility (*EARNVOL*), cash and marketable securities (*CASH*), tangibility (*TANG*), capital expenditure (*CAPEX*), Tobin's Q (*TOBINQ*), retained earnings (*RE*), return volatility (*RETVOL*), and firm risk (*BETA*).We also include industry- and year-fixed effects to control for industry-wide trends and macro-economic events. The detailed variable definitions are in Appendix A.

In matching our credit ratings and firm financial information, we use a three-month delay (i.e., the first rating issued at least three months after the fiscal year end) to ensure that firm data is available to CRAs at the time the rating is issued. Following Alp (2013), we estimate separate firm-year expected ratings for investment and speculative grades as CRAs apply different degrees of stringency across these grades. The estimation results are presented in Appendix B. These firm-year estimated ratings are then used as a firm's expected ratings in the next year (i.e., the 12 months starting from the fourth month after the firm-year end). The monthly abnormal rating is the difference between the actual and expected ratings.

From Figure 1, we see that neither CRAs nor equity market participants are able to anticipate accounting fraud more than two years ahead of its public revelation. Specifically, we see that abnormally lower ratings (stock returns) first occur around 12 (8) months prior to the public fraud revelation and then decline until the revelation date.

Examining our results further, Table 2 presents the univariate results for quarterly rating actions during the eight quarters (i.e., two years) before the class period end quarter. We label the class period end month as month 0 and the three-month period beginning on month 0 (i.e., month 0 to month 2) as the class action end quarter (i.e., *Quarter 0*). Correspondingly, month [-4, -1] is labeled as *Quarter -1*, *Quarter -2* to *Quarter -8* and is similarly defined. In our specification, we include a firm-quarter only if it overlaps with the class period of a lawsuit. That is, if a lawsuit's class period is 12 months, the case has only four firm-quarters (*Quarter -4* to *Quarter -1*) in our sample. In Table 2, we present the rating levels, rating changes, abnormal ratings, cumulative number and percentage of fraud firms that have been downgraded, and cumulative number and percentage of fraud firms that have received a negative credit watch by the end of each quarter.

Examining Table 2, we see that the fraud firms in our sample start to suffer from significantly more downgrades (column 4) and lower abnormal ratings (column 6) at least four quarters before the end of the class period. Specifically, from *Quarter -4* to *Quarter -1*, the fraud firms in our sample experience an average -0.07, -0.10, -0.17, and -0.29 decrease in ratings, respectively (all statistically significant at the 5% level or less). Furthermore, the abnormal ratings monotonically decrease from -0.01 at *Quarter -8* to -0.14 at *Quarter -4* to -0.49 at *Quarter -1*. Comparing rating actions during the quarters after versus before the fraud revelation, we see that CRAs take most rating actions against fraud firms after the fraud revelation. Specifically, the fraud firms in our sample experience significant downgrades from *Quarters 0* to *5* (*Quarters 0* to *4* for abnormal ratings), with the bulk of the downgrades occurring from *Quarters 0* to *4* (-0.92, -0.47, -0.37, -0.28, and -0.14, respectively). Cumulatively, our fraud firms experience downgrades of 0.63 (0.92, 1.34) from *Quarters -4* to *-1* (*Quarter 0*, *Quarters 1* to *4*). This observed persistence of negative rating actions may reflect a fraud firm's continued financial deterioration and/or CRAs learning more about the fraud. The results in Table 2 further show that fraud firms receive more than twice as many downgrades and negative watch list additions during *Quarters -4* to *-1* than during *Quarters -8* to *-5*. Taken together, our univariate results show that the bulk of CRAs' actions occur after the fraud revelation, but that some downgrades occur prior to the revelation.

To gain further insight into our findings, we conduct a series of regression analyses controlling for firm characteristics and other information released prior to rating actions. Here, we conduct two sets of analyses. The first analysis includes only fraud firms and covers the entire class period as well as the year prior to its beginning. In this analysis, we use the fraud firm's class period as the treatment period and the four quarters prior to the beginning of the class period as the control period. Using fraud firms as their own control mitigates the concern that fraud firms differ fundamentally from non-fraud firms. In the second analysis, we use Propensity Score Matching (PSM) to match each fraud firm with a non-fraud firm with similar firm characteristics, to better control for market-wide time trends in ratings properties and ascertain that CRAs' negative actions against fraud firms are due to the fraud itself rather than fraud firms' deteriorating economic fundamentals.

We estimate the following Eq. (1) and (2) for our first and second analyses respectively:

$$RatingActions = \alpha + \sum_{i=-8}^{-1} \beta_i \cdot Qtri + \beta_j \cdot Qtrj + \delta \cdot Controls\_RatingActions + \varepsilon \qquad (1)$$

$$RatingActions = \alpha + \sum_{i=-8}^{-1} \beta_i \cdot Qtri + \beta_j \cdot Qtrj + \sum_{i=-8}^{-1} \gamma_i \cdot Qtri * FRAUD$$
$$+\gamma_j \cdot Qtrj * FRAUD + \delta \cdot Controls\_RatingActions + \varepsilon, \qquad (2)$$

Where *Qtri* and *Qtrj* are indicator variables for the eight quarters before the fraud revelation and the rest of the class period, respectively. *FRAUD* is an indicator that equals one for fraud firms, and zero otherwise. Our dependent variables include the following rating actions: *RATE*, the level of ratings; *DG*, an indicator variable that equals one if the credit rating is downgraded in the current quarter relative to the prior quarter, and zero otherwise; and *NW*, an indicator variable that equals one if the firm receives a negative credit watch in the current quarter, and zero otherwise. We estimate an Ordered Probit model when the dependent variable is *RATE* and a Probit model when the dependent variable is *DG* or *NW*

Because we are interested in whether CRAs possess private information compared to other market participants, we control for the following other information sources: expected default frequency (*EDF*), the prior quarter's abnormal buy-and-hold returns (*RETURN*), and the abnormal short interest (*ABSI*). We also include in our specification firm characteristics used to predict abnormal ratings (presented in Appendix B). We obtain our stock price/return data from CRSP and firm-level accounting data from Compustat. All variables are measured at the beginning of each firm-quarter. Standard errors of the coefficient estimates are clustered by firms.

Table 3 presents the regression results for Eq. (1) which uses the sample that only includes fraud firms. We separately report results for regressions that do not and do control for abnormal short interest (*ABSI*) in columns (1) - (3) and columns (4) – (6) respectively, because not all sample firms have short interest data. Both sets of results show that, controlling for publicly-available information, CRAs express their negative views on fraud firms' credit worthiness as early as four to five quarters prior to the fraud revelation, consistent with those in Table 2. Specifically, we see that CRAs are significantly more likely to downgrade or issue a negative watch for fraud firms in almost each of the four quarters prior to the fraud revelation (all are statistically significant at the 5% level except for the insignificant coefficient in *Quarter -3*). We find similar results for the level of ratings: that is, fraud firms receive lower ratings as early as five quarters prior to the revelation date (all statistically significant at the 5% level or less). These results are both statistically and economically significant. For example, CRAs are 3.2%, 1.2%, 4.6%, and 6.1% more likely to downgrade fraud firms in *Quarters -4, -3, -2* and *-1*, respectively, compared to fraud firms' benchmark period (four quarters prior to the class period). These represent 40%, 15%, 57%, and 75% of the unconditional likelihood of a downgrade across all firm-quarters in the fraud sample (8.1%). Similarly, we find that CRAs are 4.7%, 4.1%, 5.3%, and 6.4% more likely to issue a negative credit watch to fraud firms in *Quarters -4, -3, -2* and *-1*, respectively, compared to the unconditional likelihood of a negative credit watch across all firm-quarters in the fraud sample (5.7%). The estimated coefficients of the control variables are consistent with our expectations. That is, firms with higher expected default frequency, lower stock returns, and higher abnormal short interest are more likely to experience negative rating actions.

Chen (2016) finds that banks charge higher interest rates and impose more demanding non-price terms for new loans issued during the accounting misstatement period. To control for information about fraud that CRAs may obtain from bank loan contracts, we include a dummy variable to indicate the issuance of a new bank loan during the last quarter. Similarly, to control for information CRAs may obtain from CDS trading (Hull et al. 2004), we include a dummy variable to indicate the presence of CDS trading during the class period. Untabulated results suggest that our inferences remain after controlling for these variables.

In our second set of regression analysis, we match each fraud firm with a non-fraud firm with similar economic fundamentals using Propensity Score Matching (PSM). Doing so, we are able to conclude that our observed negative actions against fraud firms are due to the fraud itself rather than to the firm's deteriorating economic fundamentals. We conduct PSMs using three different periods of firm characteristics. For all matching criteria, we use 0.01 as the matching caliber and exclude from our analysis those fraud firms that do not have a matched non-fraud firm.

For our first PSM, we match on firm characteristics, including industry (two-digit NAICS code), interest coverage (*INTCOV*), profitability (*PM*), total leverage (*LEV*), firm size (*SIZE*), return volatility (*RETVOL*), and firm risk (*BETA*), for the fiscal year immediately before the beginning of the class period. This method assumes that firms with comparable economic fundamentals before the fraud begins will receive similar rating actions during the fraud period.

Using this method, we obtain 208 matched pairs. Similar to our Table 3 analysis, the testing period for this matched sample covers the whole class period plus the four quarters prior to the beginning of the class period. Here, we examine whether rating changes from the pre-class period to the class period differ for fraud and matched non-fraud firms.

In our second PSM, we match fraud and non-fraud firms on both their industry and the *changes* in the aforementioned firm characteristics during the two-year period prior to fraud revelation, to control for changes in the economic fundamentals of fraud firms immediately before the fraud revelation. We choose two years as the matching window because our analysis in Table 3 shows that fraud firms do not receive negative rating actions prior to two years before the fraud. Using this method, we obtain 170 matched pairs. The testing period for this matched sample covers the nine quarters before the fraud revelation.

In our third PSM, we match each fraud firm-quarter during the two years before the fraud revelation with a non-fraud firm-quarter with similar firm fundamentals and stock returns during the last quarter. Including recent stock returns in the matching criteria further alleviates the concern that fraud and non-fraud firms differ in ways not captured by their financial statements that may affect our results. Different from the previous two methods, this method allows a fraud firm to be matched with different non-fraud firms during the testing period, which covers the nine quarters before the fraud revelation. Using this method, we obtain 2,111 matched firm-quarter pairs.

Table 4 reports the results for our matched sample analyses. Panel A compares firm characteristics between matched fraud and non-fraud firms based on alternative matching criteria. Mean and median tests show that our fraud and non-fraud firms do not differ significantly on firm characteristics, validating our matching procedures. Panels B-D report the regression results from estimating Eq. (2) for the three matching samples, respectively. We find that our matched sample analyses yield results similar to those of our main analyses. That is, CRAs are more likely to take negative actions, including lower ratings, rating downgrades and negative credit watches, against fraud firms prior to fraud revelation, compared to actions taken in regards to non-fraud firms.[10] These results are both statistically and economically significant. For example, for the sample matched on pre-fraud economic fundamentals (Panel B), the cumulative likelihood of receiving a rating downgrade (a negative credit watch) in the four quarters prior to revelation date is 5.3% (4.0%) higher for fraud firms compared to matched non-fraud firms when the unconditional probabilities of a downgrade (negative credit watch) for the matched sample are 6.7% (4.7%).

To provide further support for our conjecture that negative rating actions are due to firm fraud rather than deteriorating firm financials, we explore whether CRAs act similarly when a firm's default probability is relatively low. If CRA actions are driven by fraud detection, we expect that fraud firms with low financial distress will also receive negative rating actions. To conduct our analyses, we begin with the three sets of matched samples described above. For the first two sets of matched samples, we consider all firm-years in the class period. For the sample matched on quarterly economic performance and stock returns during the two years prior to fraud revelation, we consider all firm-quarters covered in the two-year period. We partition all fraud and non-fraud firm-years (firm-quarters) into two groups based on the sample-wide median value of EDF and tabulate the rating actions for the 2×2 matrix in Table 5.

From Table 5, we note two patterns. First, as expected, CRAs are more likely to downgrade or issue negative watches against firms with a higher level of financial distress, regardless of whether these firms have committed accounting fraud. For the sample matched on pre-fraud economic status, we see in Panel A that the probability of a negative rating action is 41% (31%)

[10] As a robustness check, for all the matched sample analyses, we control for the presence of CDS and the issuance of new bank loans during the prior quarter for both fraud and non-fraud firms; our inference continues to hold.

for distressed fraud (non-fraud) firms, compared to 18% (13%) for the respective non-distressed firms (differences significant at the 5% and 10% levels between high and low financial distress firm-years for fraud and non-fraud firms, respectively). We observe a comparable trend for the other two matched samples (Panels B and C). Second, controlling for financial distress, we find that CRAs are more likely to take negative rating actions against firms that commit fraud compared to those that do not. More importantly, this pattern continues to hold for low-distress firms (18% versus 13%, 19% versus 10%, and 8% versus 4% in Panels A, B, and C, respectively, all differences significant at the 10% level or less). Thus, even among relatively healthy firms where economic fundamentals are not as important in determining ratings, we find that CRAs still issue more negative actions against fraud firms, suggesting that fraud is likely a significant factor in the decision to issue a negative rating action.

Taken together, the results in this section show that CRAs take negative rating actions against fraud firms four to five quarters prior to the public revelation of the fraud, and that these actions are at least partly due to the fraud itself.

4.2 Analyses of the timing of negative rating actions prior to fraud revelation

In Section 4.1, we document that, on average, CRAs downgrade fraud firms or put them on negative watch at least four to five quarters prior to the fraud revelation. However, our findings also show that CRAs do not take actions against all fraud firms. Indeed, only 38% (30%) of fraud firms receive downgrades (negative credit watch) during the eight quarters prior to the fraud revelation). Furthermore, for firms receiving a negative action, the timing of the action varies (e.g., 6.95%, 5.41%, 5.79%, and 6.95% in *Quarters -4* to *-1*, respectively). In this section, we investigate the determinants of the timing of CRAs' negative rating actions against fraud firms. In particular, we examine how fraud characteristics, other sophisticated information users in the market, and CRAs' conflicts of interest influence when a negative rating action is taken.

Regarding fraud characteristics, we examine the type of fraud and its duration, severity, and complexity. With respect to the type of accounting misstatements that CRAs are more likely to detect, we draw insight from Kraft's (2015) discussion of Moody's adjustment of accounting numbers (e.g., off-balance-sheet liabilities and non-recurring items) in order to mitigate limitations in accounting standards. The descriptive data in Kraft (2015, Table 2) show that, within the items subject to adjustments, PPE, long-term debt, and operating profits are the most frequently-adjusted balance sheet and income statement accounts, adjusted in virtually all sample firm-years, while accounts receivable and revenue are the least frequently-adjusted balance sheet and income statement accounts (12% and 1.1% of the sample, respectively).[11] We expect CRAs to pay more attention to accounts that they adjust more frequently and thus be more capable in detecting frauds that involve those accounts in a timely manner.

For fraud duration, severity and complexity, on the one hand, the longer a fraud lasts (*DURATION*, the number of quarters that a class period covers) or the more severe or complex a fraud is (measured using a settlement dummy, *SETTLE*, and the number of accounts it misstates, *#MIS_ACCT*, respectively), the more likely managers are to have carefully planned and executed the fraud and the longer it might then take a CRA to detect the fraud. On the other hand, it may be more challenging and costly for managers to fabricate records and keep such frauds hidden. In this case, CRAs may have more opportunities to detect them.

Regarding the impact of other sophisticated information users, on the one hand, sophisticated information users, such as financial analysts, short sellers, or banks, may lower the information

[11] Adjustments to Accounts Receivable typically reflect the addition of accounts receivable that were securitized or otherwise transferred but where the firm retains some economic exposure.

acquisition costs for CRAs, exposing them to better quality information and making it easier for them to detect fraud. On the other hand, these same sophisticated information intermediaries may possess more expertise, financial incentives, and resources than do CRAs. This advantage can allow them to detect fraud more quickly, making it less likely that CRAs will respond to fraud prior to its revelation. To capture the presence of sophisticated information users, we include analyst following, short sellers' presence, the issuance of new bank loans, and CDS trading activities.

Last, we explore the effect of rating agencies' conflicts of interest. Prior research shows that the presence of heightened competition from other rating agencies such as Fitch, S&P and Moody's suffer from more conflicts of interest, and issue lower quality ratings, i.e., the ability of ratings to predict default deteriorates. Thus, we expect that CRAs will be less willing to take negative rating actions against issuers when the competition is higher. Following Becker and Milbourn (2011), we measure rating agency competition using Fitch's market share in an industry, i.e., the proportion of outstanding bonds rated by Fitch. A higher Fitch share indicates a higher level of competition among rating agencies.

Table 6 presents the results. For this set of analyses, our sample consists of our full set of 259 fraud events. The dependent variable is the number of quarters between the earliest date that a fraud firm suffers a rating downgrade or receives a negative credit watch during the two years before the fraud revelation (or during the class period if the class period is shorter than two years) and the fraud revelation date. If a fraud firm does not suffer any negative rating actions during this window, the variable is set to zero. Therefore, the dependent variable ranges from zero to eight, with greater values indicating that CRAs take more timely rating actions.[12] We estimate an ordered

[12] In a sensitivity test, we use an indicator variable of whether CRAs take negative rating actions prior to public fraud revelation as our dependent variable and find similar results (untabulated).

Probit model controlling for the sample-period mean value of firm characteristics outlined in Table 3 as well as year- and industry-fixed effects (where year is defined as the class period end year).

Column (1) presents the results from our analysis of the effect of fraud type on rating actions. *REVENUE*, *INVT*, *AR*, *PPE*, *INTANGIBLE*, *EXPNESE*, *LIABILITY*, *MA* are dummy variables indicating misstatements of the following items: revenue, inventory and cost of goods sold, accounts receivable and bad debt allowance, long-term tangible assets and impairment, intangible assets and impairment, operating profits, liabilities, and accounts involving mergers and acquisitions effects, respectively. The results show a significant positive effect of misstatements of long-term tangible assets, intangible assets, and liabilities accounts on the timeliness of negative rating actions, consistent with CRAs' attention on long-term assets and liabilities (Kraft, 2015).

Column (2) reports the effects of fraud length, severity and complexity on the timing of a negative rating action. The results show that the timeliness of a negative rating action is positively associated with both the fraud duration and whether the case is settled, consistent with the perspective that CRAs issue negative rating actions earlier against firms that have committed more severe fraud. We do not find any effects on the number of misstated accounts misstated.

In column (3), we present the results of our analysis of the effect of other sophisticated information users on the timeliness of rating actions. Here, we measure analyst following at the beginning of the class period (or two years prior to the fraud revelation for frauds that last longer than two years) and short sellers' presence as the maximum level of abnormal short interest during the class period (or the two years prior to the fraud revelation for frauds that last longer than two years). We also include two indicator variables of whether, during the class period (or the two years prior to fraud revelation for frauds that last longer than two years), there is any issuance of new bank loans (*LOAN*) or CDS trading (CDS). The results show that the coefficient on *ABSI* is significantly positive, indicating that fraud firms are more likely to suffer a downgrade or negative watch when they experience abnormally high short interest. By contrast, our results show no significant relation between analyst following, the issuance of bank loans, or the presence of CDS trading and the timeliness of negative rating actions.

Column (4) examines the impact of CRA competition on rating actions. To measure competition, we use the Fitch market share at the beginning of the class period for each fraud instance (or two years prior to fraud revelation for frauds that last longer than two years) for the industry that the fraud firm belongs to. The results show no statistically significant relationship between the timing of a rating action and the corresponding Fitch market share. We interpret this lack of an observed relation to either our small sample size or CRA concerns about the reputational consequences of failing to incorporate fraud information into their credit ratings.

Finally, Column (5) presents the results when we include all factors in our specification. Doing so, we find that *DURATION*, *SETTLE*, *PPE*, *INTANGIBLE*, *LIABILITY*, and *ABSI* all remain significant. Taken together, we use the results in this section to conclude that CRAs take earlier negative rating actions against fraud cases that are more severe, that involve accounting items most frequently scrutinized by CRAs, and that are targeted by short sellers.

5. Economic Impact of Rating Actions against Fraud Firms

In our final set of analyses, we investigate the economic impact of CRAs' negative rating actions against fraud firms. Specifically, we study market reactions to rating actions as well as the relation between rating actions and fraud duration.

5.1 Market reactions to rating actions against fraud firms before fraud revelation

To examine market reactions to negative rating actions, we focus on the equity market rather than the bond market because equities are more liquid and using equity market data allows us to capture investor reactions to negative rating actions in a more timely manner. On the other hand, many bonds do not trade around rating changes.[13]

To address the concern that any observed relation may reflect a CRA's response to a firm's financial deterioration, we again use a matching procedure to match each fraud firm's rating event with a rating event of the same severity against a non-fraud firm. In particular, we select the matched non-fraud rating events using the following procedure. First, for each rating downgrade (negative credit watch), we identify all non-fraud firms from the same industry (two-digit NAICS code) that also suffer a rating downgrade (negative credit watch) within one year around the fraud firm's rating event. Next, we choose the non-fraud rating event where the magnitude of the rating downgrade is closest to that experienced by the fraud firm. In addition to matching on negative action magnitude, we choose the non-fraud rating event where the non-fraud firm's rating is closest to that of the matched fraud firm. Last, we choose the non-fraud rating event whose date is the closest to that of the fraud rating event. Our final sample consists of 130 pairs of rating downgrades and 93 pairs of negative credit watches.

Panel A of Table 7 presents the descriptive statistics for our matched pairs. From Panel A, we see that both the magnitude of rating downgrades (Δ*RATE*) and the most recent ratings before the rating actions (*LAG_RATE*) are similar for our fraud and non-fraud firms, confirming that our matching procedures are effectiveness. We also see that market reactions (*CAR[-1,1]*) to rating downgrades and negative credit watches are more negative for fraud firms than for non-fraud firms (differences in the mean values are significant at the 10% and 5% level, respectively).

[13] The sample does not include sufficient CDS spread data to examine the CDS response to rating actions.

Panel B presents the regression results. Column (1) reports the market reactions to rating downgrades. To control for non-linearity in the market reaction to a rating change conditional on the rating level beforehand, we include the interaction between the rating change and the lagged rating ($\Delta RATE \times LAG\_RATE$) in our estimation. The results show that the coefficient on $\Delta RATE$ is significantly positive, suggesting that the market reacts negatively to rating downgrades of non-fraud firms. We further observe that the coefficient on the interaction term ($\Delta RATE \times FRAUD$) is insignificant, suggesting that the market reacts similarly to the same rating downgrade magnitude for fraud and non-fraud firms. In our earlier analyses, we find that, *after controlling for economic fundamentals*, fraud firms suffer incremental rating downgrades prior to fraud revelation. While the coefficient on $\Delta RATE$ measures the information content of downgrades due to deteriorating fundamentals of non-fraud firms, the sum of coefficient on $\Delta RATE$ and $\Delta RATE \times FRAUD$ measures the information content of downgrades due to both fraud and deteriorating fundamentals in fraud firms. Put together, our finding of an insignificant coefficient for $\Delta RATE \times FRAUD$ indicates that the market finds fraud-related downgrades as informative as those attributed to a firm's deteriorating economic fundamentals.

Column (2) reports our results for market reactions to negative credit watches. In this regression, we include only *FRAUD* and *LAG_RATE* as negative credit watches are not multilayered. The results show that the intercept is insignificantly different from zero, indicating that the market does not react when non-fraud firms receive a negative credit watch. By contrast, both the coefficient on *FRAUD* and its sum with the intercept are significantly negative, indicating that the market not only finds fraud firm credit watches informative, but also finds the components of the credit watches that can be attributable to fraud more informative than those driven by economic fundamentals. Overall, our analyses in this section suggest that the market finds rating actions against fraud firms prior to fraud revelation to be informative.

5.2 Negative rating actions and fraud duration

In our final analysis, we examine whether rating actions shortens fraud duration. Following Karpoff and Lou (2010), we use survival models that measure how rating status or actions affect the time it takes from fraud initiation to its public revelation. In particular, we model the logarithm of the time to revelation, log(M_i), as:

$$log(M_i) \ = \ \beta' X_i + \varepsilon_i$$

Where M_i is the number of quarters from the start until the end of the class action period of fraud i, X_i is the vector of possibly time-varying covariates assumed to influence the time until public revelation, and β is a vector of estimated regression parameters.

In estimating the above model, we use data from all quarters between the class period start and end dates. The explanatory variables, X_i, are measured at the beginning of each quarter t. For each quarter t, we observe the following vector [t, $Revelation_{i,t}$, X_i], where $Revelation_{i,t}$ is a dummy variable that equals one if fraud i is revealed in quarter t, and zero otherwise. Doing so, we are able to construct a log-likelihood function to estimate the parameter vector β. In the data matrix X_i, our main variables of interest are level of ratings and rating actions, including credit ratings, abnormal credit ratings, whether a firm-quarter suffers a rating downgrade, and whether a negative watch is issued for the firm-quarter. In our specification, we also include controls for abnormal short interest (*ABSI*), firm size (*SIZE*), Tobin's Q (*TOBINQ*), leverage (*LEV*), profit margin (*PM*), return volatility (*RETVOL*), and one-year abnormal returns (*ABRET*). The results are reported in Table 8.

In Table 8, columns (1) - (4) and columns (5) - (8) present the results for regressions without and with abnormal short interest as a control variable respectively. Both results show that the time horizon for fraud revelation is significantly positively associated with both the ratings levels (columns 1 and 5) and abnormal ratings (columns 2 and 6), indicating that lower ratings are associated with shorter revelation times. This result is both statistically and economically significant. For example, holding all other variables at the mean, a decrease in a fraud firm's abnormal rating from the sample median (*ABR* = 0) to the 25th percentile (*ABR* = -1.00) shortens the fraud duration by 1.1 quarters, or 13% of the average fraud length (the mean time-to-revelation is 8.3 quarters, as reported in Table 1, Panel B). Columns (3) - (4) and (7) – (8) show a similar effect on fraud revelation time for a downgrade or negative credit watch, indicating that negative rating actions shorten the time taken to reveal a misstatement. The last four columns also show that abnormal short interest (*ABSI*) is significantly negatively associated with fraud duration, consistent with the finding of Karpoff and Lou (2010). Comparing results in the first and the last four columns, we further conclude that the economic significance of rating actions does not diminish when we control for short interest, suggesting that short sellers and CRAs likely play independent roles in fraud revelation.

Taken together, our analyses in Section 5 show that negative rating actions against fraud firms contain information about accounting fraud beyond that provided by other market participants and that these actions help expose the fraud in a more timely manner.

6. Conclusion

This study examines whether and when CRAs take negative rating actions against fraud firms before the fraud is publicly revealed. It also examines the economic consequences of these actions.

Using a sample of 259 securities class-action lawsuits against firms engaging in accounting misstatements from 1996 to 2016, we first find that fraud firms experience lower ratings, a greater likelihood of being downgraded, and a greater likelihood of receiving a negative credit watch during the four quarters prior to fraud revelation. These results hold when controlling for the firms' economic fundamentals, and for fraud firms not in financial distress. Second, we find that CRAs take more timely rating actions when the fraud is more severe, when it involves accounting items more likely to be examined by CRAs, and when the fraud firms experience abnormally high short interest. Last, we find that the market finds negative rating actions to be informative and that these actions are associated with a shorter duration of fraud periods.

Overall, our findings lend support for the conjecture that CRAs' rating actions likely contain private information regarding an issuer's financial fraud and these actions inform investors. While CRAs may not explicitly view their role as one of fraud detection, we show that their rating actions nonetheless facilitate the uncovering of certain types of fraud.

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Appendix A: Variable Definitions

Tables 3 and 4: Dependent variables and firm characteristics	
ABR	Abnormal rating at the end of a firm-quarter. Abnormal rating is calculated as the difference between actual rating and rating predicted from the ordered probit model specified in Appendix B.
DG	Dummy variable set to one if a firm-quarter experiences a rating downgrade and zero otherwise.
NEW	Dummy variable set to one if a firm-quarter receives a negative credit watch and zero otherwise.
EDF	Expected default frequency at the beginning of a firm-quarter. *EDF* is calculated every month based on quarterly accounting variables and monthly market values following Bharath and Shumway (2008).
RETURN	Market-adjusted buy-and-hold return of last firm-quarter.
ABSI	Abnormal short interest at the beginning of a firm-quarter. Normal short interest is defined as shares held for shorting divided by shares outstanding at the end of every month. *ABSI* is estimated every month following Karpoff and Lou (2010).
INTCOV	The ratio of EBITDA to interest expense of the most recent fiscal year prior to a firm-quarter.
PM	The ratio of EBITDA to revenue of the most recent fiscal year prior to a firm-quarter.
LTLEV	The ratio of long-term debt to total assets of the most recent fiscal year prior to a firm-quarter.
LEV	The sum of long-term and short-term debt to total assets of the most recent fiscal year prior to a firm-quarter.
SIZE	Logarithm of total assets in million of U.S. dollars.
DEBT/EBITDA	The ratio of the sum of long-term and short-term debs to EBITDA of the most recent fiscal year prior to a firm-quarter.
NEG_DEBT/EBITDA	Dummy variable set to one if DEBT/EBITA is negative and zero otherwise.
EARNVOL	The standard deviation of profit margin (PM) in the five years prior to a firm-quarter.
CASH	The ratio of cash to total assets of the most recent fiscal year prior to a firm-quarter.
TANG	The ratio of PPE (net) to total assets of the most recent fiscal year prior to a firm-quarter.
CAPEX	The ratio of capital expenditure to total assets of the most recent fiscal year prior to a firm-quarter.
TOBINQ	The ratio of the sum of total liability and market value of equity to total assets of the most recent fiscal year prior to a firm-quarter.
RE	The ratio of retained earnings to total assets of the most recent fiscal year prior to a firm-quarter.
RETVOL	The standard deviation of daily residual returns during the year prior to the beginning of a firm-quarter, where the daily residual return is obtained by regressing daily stock return on daily value-weighted market index return.
BETA	The coefficient of regressing daily stock return on daily value-weighted market index return during the year prior to a firm-quarter.

Table 6: Determinants of rating actions before fraud revelation

TIME	The number of quarters between the earliest date that a fraud firm suffers a rating downgrade or receives a negative credit watch during two years before fraud revelation.
DURATION	Number of quarters that a class period covers.
SETTLE	Dummy variable set to one if a case is settled and zero otherwise.
#MIS_ACCT	Number of misstated accounts.
REVENUE	Dummy variable set to one if a fraud involves misstatement in revenue and zero otherwise.
AR	Dummy variable set to one if a fraud involves misstatement in accounts receivable or allowance for doubtful accounts and zero otherwise.
INVT	Dummy variable set to one if a fraud involves misstatement in inventory or cost of goods sold and zero otherwise.
PPE	Dummy variable set to one if a fraud involves misstatement in the value, depreciation or impairment of long-term tangible assets and zero otherwise.
INTANGIBLE	Dummy variable set to one if a fraud involves misstatement in the value, amortization or impairment of intangible assets and zero otherwise.
LIABILITY	Dummy variable set to one if a fraud involves misstatement in liabilities or payables and zero otherwise.
EXPENSE	Dummy variable set to one if a fraud involves misstatement in operating expense or improper capitalization of expense and zero otherwise.
MA	Dummy variable set to one if a fraud involves misstatement in mergers and acquisitions and zero otherwise.
#ANALYST	Logarithm of one plus number of analysts during the year prior to the start of a class period (if the class period is less than two years) or prior to the eight-quarter period before the class period ends (if the class period is equal to or longer than two years).
ABSI	The maximum level of abnormal short interest during the class period (or the two years prior to fraud revelation for frauds lasting longer than two years).
LOAN	Dummy variable set to one if new bank loans were issued during the class period (or the two years prior to fraud revelation for frauds lasting longer than two years).
CDS	Dummy variable set to one if CDS was traded on issuer's debt during the class period (or the two years prior to fraud revelation for frauds lasting longer than two years).
FITCH	Fitch's market share in an industry-year prior to the start of a class period (if the class period is less than two years) or prior to the eight-quarter period before the class period ends (if the class period is equal to or longer than two years). The market share of an industry-year is calculated as the proportion of outstanding bonds rated by Fitch in that industry-year where the industry classification is based on 2-digit NAICS code.

Table 7: Market reactions to rating actions

CAR[-1,1]	Three-day cumulative, market-adjusted returns around the rating action date.

Δ*RATE*	The difference between current rating and most recent rating prior to current rating.
LAG_RATE	The recent rating prior to current rating action.

Appendix B: Estimation of Abnormal Ratings

This appendix presents the estimation of abnormal ratings for Compustat firm-years with S&P long-term issuer ratings during 1991 and 2016. Abnormal rating is the difference between the actual rating and the expected rating, which is the predicted rating category with the highest fitted probability from the Ordered Probit model. We estimate the Ordered Probit model separately for firm-years with investment grade (i.e., BBB- and above) and speculative grade (i.e., below BBB-). Variable definitions are in Appendix A. Standard errors of the coefficient estimates are clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent variables:	*RATE*	
	Investment grade	Speculative grade
	(1)	(2)
INTCOV	0.003**	0.001
	(2.38)	(1.44)
PM	0.903***	0.096
	(5.76)	(0.69)
LTLEV	-3.767***	0.690***
	(-8.47)	(3.38)
LEV	1.880***	-1.262***
	(4.22)	(-5.89)
SIZE	0.428***	0.353***
	(14.90)	(16.75)
DEBT/EBITDA	-0.027**	-0.034***
	(-2.52)	(-11.75)
NEG_DEBT/EBITDA	0.409	-0.909***
	(1.39)	(-8.57)
EARNVOL	-2.654***	-0.490***
	(-3.34)	(-5.13)
CASH	0.268	-1.134***
	(1.04)	(-7.12)
TANG	0.358*	-0.329***
	(1.85)	(-2.71)
CAPEX	0.875*	0.188
	(1.65)	(0.64)
TOBINQ	0.338***	0.249***
	(11.05)	(11.87)
RE	1.521***	0.540***
	(12.22)	(10.16)
RETVOL	-39.161***	-36.177***
	(-10.45)	(-26.25)
BETA	-0.422***	-0.059**
	(-8.39)	(-2.25)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
#Firm-years	14,773	14,386
Pseudo R^2	0.16	0.17

Figure 1: Equity Market Reaction and Rating Actions before Fraud Revelation

This figure presents the monthly ratings (*RATE*), abnormal ratings (*ABR*) and monthly cumulative abnormal buy-and-hold returns (*ABRET*)during the 24 months before fraud revelation for the 259 sample fraud events. Numbers in bold indicates significance at 10% level or less. Variable definitions are presented in Appendix A.

	#Cases	RATE	#Cases	ABR	t-value	#Cases	ABRET	t-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-24	214	11.514	202	0.015	0.16	250	-0.001	-0.16
-23	217	11.479	204	-0.025	-0.26	252	0.005	0.43
-22	220	11.441	206	-0.005	-0.05	252	0.018	1.20
-21	222	11.405	208	-0.043	-0.47	253	0.011	0.67
-20	222	11.396	209	-0.057	-0.64	254	0.026	1.29
-19	225	11.351	212	-0.042	-0.48	254	0.032	1.40
-18	226	11.327	212	-0.042	-0.48	254	0.019	0.75
-17	228	11.307	215	-0.037	-0.43	255	0.010	0.39
-16	230	11.309	219	-0.037	-0.41	255	0.005	0.20
-15	229	11.293	218	-0.073	-0.82	255	-0.001	-0.02
-14	233	11.262	220	-0.082	-0.91	256	-0.011	-0.43
-13	238	11.185	225	-0.098	-1.10	256	0.011	0.34
-12	239	11.138	227	**-0.145**	**-1.93**	257	-0.008	-0.24
-11	241	11.100	230	**-0.148**	**-1.96**	257	-0.025	-0.70
-10	241	11.079	230	**-0.143**	**-1.91**	257	-0.030	-0.81
-9	244	11.008	233	**-0.197**	**-2.20**	257	-0.049	-1.29
-8	246	10.963	238	**-0.185**	**-2.02**	257	**-0.080**	**-2.18**
-7	246	10.951	236	**-0.216**	**-2.38**	257	**-0.091**	**-2.53**
-6	246	10.902	236	**-0.242**	**-2.72**	257	**-0.117**	**-3.30**
-5	248	10.802	238	**-0.311**	**-3.37**	257	**-0.143**	**-3.85**
-4	249	10.755	238	**-0.319**	**-3.46**	257	**-0.161**	**-4.25**
-3	251	10.701	239	**-0.343**	**-3.56**	257	**-0.182**	**-4.69**
-2	252	10.571	241	**-0.427**	**-4.12**	257	**-0.205**	**-5.16**
-1	252	10.425	240	**-0.492**	**-4.39**	257	**-0.250**	**-6.16**
0	251	10.040	237	**-0.755**	**-5.75**	257	**-0.409**	**-11.52**

Figure 1 (Continued)

Equity Market Reaction and Rating Actions before Fraud Revelation

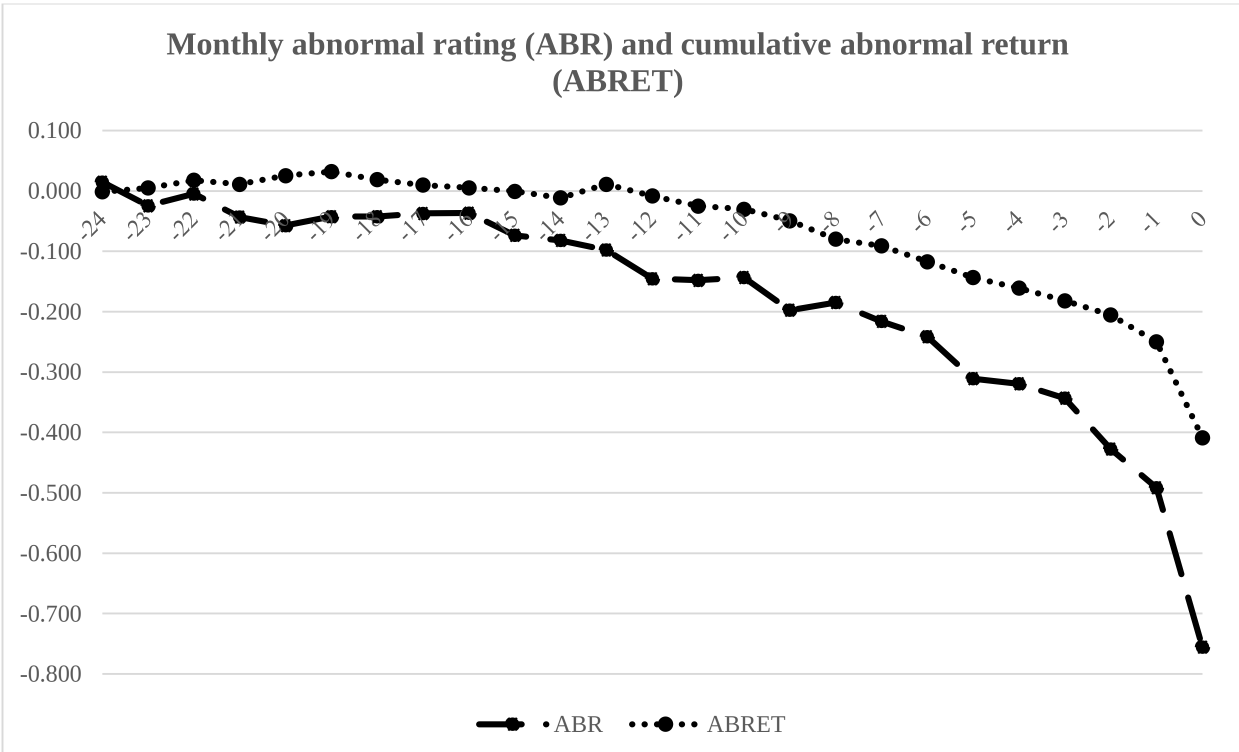

Table 1: Sample Selection Procedures and Descriptive Data

Panel A: Sample selection procedures

This panel presents the sample selection procedure for accounting frauds.

1934-10(b) cases with class period ended between 1996 and 2016 and with firm trading ticker	3,488
Cases failing to identify Compustat GVKEY (by merging ticker with GVKEY)	(128)
	3,360
Firms without S&P long-term issuer ratings during the class period	(2,210)
	1,150
Financial firms or firms without industry identity (two-digit NAICS equal to 52 or 99)	(238)
	912
Cases with class period shorter than one year	(446)
	466
Exclude: Misconducts during IPO process	(17)
Bribery to governments	(12)
Non-corporate malpractice (auditors, equity analysts or underwriters being sued)	(25)
Non-accounting malpractice (e.g., sexual harass; CEO and board disputes)	(7)
Duplicates	(4)
	401
Exclude: Cases involving misleading (forward-looking) disclosures	(142)
Final sample: Financial misconduct cases involving misstated accounting numbers	**259**
Including: Settled cases	*155*
Dismissed cases	*91*
Ongoing cases	*13*

Panel B: Sample fraud characteristics

This panel reports the characteristics of the sample frauds.

Variable	#Cases	Min	25%	Mean	Median	75%	Max
From Class Start to End (#quarters)	259	4.000	4.667	8.268	6.333	11.000	30.000
From Class End to Filing Date (#quarters)	259	0.000	0.000	1.252	0.333	1.667	12.000
From Class Start to Filing Date (#quarters)	259	4.000	5.333	9.520	8.000	12.000	32.667
Settlement Amount (millions of USD)	155	0.150	6.500	174.412	17.350	55.000	6133.000

Panel C: Sample distribution by year

This panel reports the fraud sample distribution by class period ending year.

Class Period End Year	# of Cases	% of Total Cases
1996	2	0.77%
1997	8	3.09%
1998	11	4.25%
1999	11	4.25%
2000	15	5.79%
2001	14	5.41%
2002	52	20.08%
2003	14	5.41%
2004	26	10.04%
2005	10	3.86%
2006	16	6.18%
2007	6	2.32%
2008	5	1.93%
2009	8	3.09%
2010	5	1.93%
2011	8	3.09%
2012	8	3.09%
2013	5	1.93%
2014	13	5.02%
2015	6	2.32%
2016	16	6.18%
Total	259	100%

Panel D: Sample distribution by industry

This panel reports the fraud sample distribution by industry and the industry distribution in Compustat.

NAICS2	Industry Name	Fraud Sample #	Fraud Sample %	Compustat firms with S&P ratings #	Compustat firms with S&P ratings %
11	Agriculture, Forestry, Fishing and Hunting	0	0.00%	11	0.26%
21	Mining, Quarrying, and Oil and Gas Extraction	12	4.63%	344	8.14%
22	Utilities	15	5.79%	360	8.52%
23	Construction	2	0.77%	69	1.63%
31	Manufacturing: Food, Textile, Apparel	13	5.02%	204	4.83%
32	Manufacturing: Wood, Paper, Printing, Petroleum, Chemicals, Plastics	32	12.36%	544	12.87%
33	Manufacturing: Metals, Machinery, Computers, Electrical, Furniture	57	22.01%	775	18.33%
42	Wholesale: Trade	8	3.09%	150	3.55%
44	Retail Trade: Motor Vehicles, Furniture, Electronics, Food, Gas	10	3.86%	170	4.02%
45	Retail Trade: Sporting goods, Books, Florists, Office Supplies, Mail-Order, Vending	5	1.93%	86	2.03%
48	Transportation and Warehousing: Air Transport, Water Transport, Trucks, Pipelines	12	4.63%	190	4.49%
51	Information	35	13.51%	617	14.60%
53	Real Estate and Rental and Leasing	11	4.25%	198	4.68%
54	Professional, Scientific, and Technical Services	14	5.41%	111	2.63%
56	Administrative and Support and Waste Management and Remediation Services	8	3.09%	94	2.22%
61	Educational Services	0	0.00%	3	0.07%
62	Health Care and Social Assistance	17	6.56%	98	2.32%
71	Arts, Entertainment, and Recreation	3	1.16%	50	1.18%
72	Accommodation and Food Services	3	1.16%	130	3.08%
81	Other Services (except Public Administration)	2	0.77%	23	0.54%
Total		259	100%	4,227	100%

Panel E: Type of misstated accounts identified from the "Class Action Complaint Report"

This panel presents the frequency and percentage of misstated accounts in the sample frauds.

Variable	Definition	# of Cases	% of Total Frauds
REVENUE	Revenue	146	56.37%
INVT	Inventory or cost of goods sold	39	15.06%
AR	Accounts receivable or bad debt expense	49	18.92%
PPE	Long-term tangible asset value, depreciation and impairment	50	19.31%
INTANGIBLE	Goodwill/intangible asset value, amortization and impairment	25	9.65%
LIABILITY	Liabilities, payables and reserve accounts	75	28.96%
EXPENSE	Other operating expense or improper expense capitalization	82	31.66%
SECURITIES	Market securities	5	1.93%
TAX	Tax accounts	21	8.11%
CF	Cash flow accounts	11	4.25%
CONSOL	Improper consolidation or equity methods	12	4.63%
MA	Mergers and acquisitions	27	10.42%

Panel F: Sample fraud firm characteristics

This panel presents the descriptive data for the sample firm characteristics during the class period and one year before the start of the class period. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively.

	Class period		One-year prior to class period starts		Difference	
	Mean	Median	Mean	Median	Mean (*t*-stat)	Median (*z*-stat)
	(1)	(2)	(3)	(4)	(5)	(6)
RATE	11.314	11.000	11.594	11.000	-1.94*	-1.45
DG	0.092	0.000	0.050	0.000	3.99***	3.50***
NW	0.068	0.000	0.028	0.000	4.77***	3.93***
EDF	0.137	0.010	0.101	0.002	3.81***	3.76***
RETURN	-0.026	-0.025	0.026	0.016	-5.25***	-5.16***
ABSI	0.009	-0.003	0.006	0.000	1.91*	-1.14
INTCOV	13.211	4.673	11.883	4.854	1.20	-0.51
PM	0.178	0.151	0.173	0.156	0.72	-0.78
LEV	0.354	0.354	0.358	0.360	-0.50	-0.43
SIZE	8.481	8.306	8.311	8.202	2.58***	2.41**
DEBT_EBITDA	3.913	3.106	3.633	2.946	1.11	1.35
NEG_DEBT/EBITDA	0.027	0.000	0.043	0.000	-1.92*	-2.10**
EARNVOL	0.064	0.023	0.083	0.024	-2.16**	0.42
CASH	0.092	0.050	0.092	0.046	0.07	0.63
TANG	0.295	0.230	0.319	0.269	-2.37**	-2.11**
CAPEX	0.062	0.041	0.066	0.046	-1.43	-1.56
TOBINQ	1.745	1.360	1.915	1.453	-3.05***	-3.45***
RE	0.081	0.090	0.070	0.086	0.81	0.12
RETVOL	0.027	0.024	0.026	0.023	1.90*	1.86*
BETA	1.014	0.941	1.013	0.917	0.03	0.14

Table 2: Univariate Analysis of Rating Actions before Fraud Revelation

This table presents the ratings actions against sample fraud firms during the eight quarters prior to class period end date and the seven quarters after the class period end date. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively.

Quarter	# of Cases	*RATE*	# of Cases	*ΔRATE*	# of Cases	*ABR*	# of unique cases by the quarter	cumulative number of downgrades	cumulative percentage of downgrades	cumulative number of negative watches	cumulative percentage of negative watches
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)=(8)/(7)	(10)	(11)=(10)/(7)
-8	220	11.441	217	-0.041	206	-0.005	220	10	5%	7	3%
-7	225	11.351	222	-0.036	212	-0.042	225	19	8%	16	7%
-6	230	11.309	228	-0.013	219	-0.037	231	27	12%	21	9%
-5	239	11.188	233	-0.090***	226	-0.102	241	40	17%	29	12%
-4	243	11.070	241	-0.071**	232	-0.143**	246	55	22%	36	15%
-3	247	10.923	246	-0.098**	237	-0.228**	252	67	27%	46	18%
-2	249	10.755	248	-0.169***	238	-0.319***	254	85	33%	58	23%
-1	253	10.423	252	-0.290***	241	-0.494***	259	98	38%	78	30%
0	**251**	**9.546**	**251**	**-0.924*** **	**236**	**-1.093*** **	**259**	**125**	**48%**	**115**	**44%**
1	239	9.485	239	-0.469***	222	-0.973***	259	144	56%	128	49%
2	223	9.475	222	-0.369***	206	-0.903***	259	161	62%	130	50%
3	212	9.495	212	-0.283***	195	-0.662***	259	166	64%	135	52%
4	199	9.477	199	-0.216***	181	-0.331**	259	172	66%	143	55%
5	185	9.681	183	-0.142***	171	-0.088	259	178	69%	147	57%
6	181	9.685	180	-0.072	166	-0.072	259	184	71%	150	58%
7	179	9.592	179	-0.145**	163	-0.190	259	191	74%	151	58%

Table 3: Regression Analysis of Rating Actions around Fraud Revelation

This table examines whether S&P takes negative rating actions prior to the public revelation of frauds. The dependent variable is long-term issuer ratings at the end of a firm-quarter (columns 1 & 4), a dummy variable indicating the rating downgrade during a firm-quarter (columns 2 & 5), and a dummy variable indicating the issuance of negative watch during a firm-quarter (columns 3 & 6). For every fraud case, the sample period covers the whole class period plus four quarters prior to the start of the class period. Variable definitions are in Appendix A. Standard errors of the coefficient estimates are clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables:	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Qtr_prior-8	-0.007	-0.272	-0.372*	0.011	-0.246	-0.432
	(-0.07)	(-1.60)	(-1.80)	(0.10)	(-1.35)	(-1.62)
Qtr -8	-0.123	-0.045	0.193	-0.123	-0.057	0.267
	(-1.20)	(-0.15)	(0.75)	(-1.10)	(-0.17)	(1.01)
Qtr -7	-0.084	-0.214	-0.001	-0.089	-0.159	0.030
	(-0.98)	(-0.78)	(-0.00)	(-0.98)	(-0.56)	(0.10)
Qtr -6	-0.127	-0.224	-0.291	-0.122	-0.255	-0.591
	(-1.43)	(-1.05)	(-0.89)	(-1.49)	(-1.06)	(-1.48)
Qtr -5	**-0.176****	0.091	0.212	**-0.148***	0.086	0.181
	(-2.25)	(0.47)	(1.01)	**(-1.89)**	(0.41)	(0.79)
Qtr -4	**-0.169****	**0.270****	**0.480*****	**-0.187*****	**0.294***	**0.492*****
	(-2.53)	**(2.01)**	**(2.72)**	**(-2.63)**	**(1.80)**	**(2.60)**
Qtr -3	**-0.187*****	0.104	**0.419****	**-0.160****	0.152	**0.429****
	(-2.62)	(0.61)	**(2.26)**	**(-2.14)**	(0.82)	**(2.17)**
Qtr -2	**-0.193*****	**0.388****	**0.546*****	**-0.176****	**0.427****	**0.576*****
	(-2.67)	**(2.46)**	**(3.49)**	**(-2.27)**	**(2.55)**	**(3.40)**
Qtr -1	**-0.253*****	**0.518*****	**0.656*****	**-0.234****	**0.585*****	**0.641*****
	(-3.01)	**(3.54)**	**(4.26)**	**(-2.47)**	**(3.76)**	**(4.10)**
Qtr 0	**-0.441*****	**0.848*****	**1.207*****	**-0.386*****	**0.835*****	**1.158*****
	(-4.31)	**(6.16)**	**(8.02)**	**(-3.45)**	**(5.71)**	**(7.51)**
EDF	-0.206	1.072***	0.514**	-0.229	1.033***	0.333
	(-0.78)	(4.58)	(1.98)	(-0.76)	(4.20)	(1.18)
RETURN	0.246**	-0.977***	-0.547***	0.362***	-1.027***	-0.645***
	(2.35)	(-5.73)	(-2.86)	(2.92)	(-5.03)	(-2.84)
ABSI				-2.336***	1.723***	0.715
				(-2.80)	(2.66)	(1.11)
INTCOV	0.000	-0.003	-0.001	-0.001	-0.003	-0.002
	(0.01)	(-0.87)	(-0.56)	(-0.29)	(-0.76)	(-0.69)
PM	0.264	-0.600	-1.236***	-0.244	-0.336	-1.611***
	(0.44)	(-1.25)	(-2.59)	(-0.35)	(-0.62)	(-3.07)
LEV	-1.900***	0.807**	-0.042	-1.495**	0.458	0.061
	(-3.93)	(2.15)	(-0.11)	(-2.48)	(0.96)	(0.14)
SIZE	0.623***	0.074**	-0.016	0.618***	0.078**	-0.015

	(10.79)	(2.09)	(-0.39)	(9.63)	(2.18)	(-0.35)
DEBT_EBITDA	-0.031***	-0.007	0.000	-0.065**	0.010	-0.010
	(-2.71)	(-0.76)	(0.01)	(-2.42)	(0.78)	(-0.70)
NEG_DEBT/EBITDA	-0.144	-0.396	-0.092	-0.638	-0.672	-0.212
	(-0.32)	(-0.92)	(-0.20)	(-0.95)	(-1.08)	(-0.41)
EARNVOL	-0.845***	-0.578**	-0.282	-0.657*	-0.521*	-0.159
	(-2.96)	(-2.16)	(-0.97)	(-1.69)	(-1.82)	(-0.42)
CASH	-0.847	0.208	0.746	-0.614	-0.035	0.340
	(-1.55)	(0.38)	(1.36)	(-0.86)	(-0.05)	(0.54)
TANG	-0.347	1.059***	0.542	-0.281	1.277***	0.633
	(-0.75)	(3.09)	(1.40)	(-0.57)	(3.59)	(1.56)
CAPEX	-1.498	-1.704*	-0.693	-2.127	-1.651	-1.224
	(-1.10)	(-1.74)	(-0.55)	(-1.38)	(-1.51)	(-0.89)
TOBINQ	0.250***	-0.181**	-0.062	0.274***	-0.186**	-0.017
	(4.51)	(-2.44)	(-0.96)	(3.98)	(-2.12)	(-0.25)
RE	1.608***	0.191	0.209	1.843***	0.048	-0.014
	(5.76)	(0.92)	(1.16)	(5.76)	(0.19)	(-0.07)
RETVOL	-37.894***	1.129	-4.097	-42.696***	-5.851	-6.737
	(-5.20)	(0.20)	(-0.56)	(-5.14)	(-0.96)	(-0.90)
BETA	-0.335**	0.015	-0.034	-0.363**	0.107	0.008
	(-2.54)	(0.16)	(-0.31)	(-2.52)	(0.91)	(0.06)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
#Firm-quarters	2,721	2,721	2,568	2,338	2,314	2,189
Pseudo R^2	0.30	0.23	0.18	0.31	0.24	0.19

Table 4: Regression Analysis of Rating Actions around Fraud Revelation-Matched Sample

This table compares the rating actions between fraud and matched non-fraud firms prior to the fraud revelation. Panel A compares firm characteristics between fraud and matched non-fraud firms under alternative matching criteria. Panel B presents the regression estimates for the difference in rating actions between fraud and non-fraud firms during the class period, where the two groups of firms are matched on industry and firm characteristics during the year prior to the start of the class period. Panel C presents the regression estimates for the difference in rating actions between fraud and non-fraud firms during two years prior to fraud revelation, where the two groups of firms are matched on industry and changes in firm characteristics during the two years prior to fraud revelation. Panel D presents the regression estimates for the difference in rating actions between fraud and non-fraud firms during two years prior to fraud revelation, where the two groups of firms are matched on industry and firm-quarter economic performance and lagged stock returns. For Panels B-D, the dependent variable is the long-term issuer rating at the end of a firm-quarter (columns 1 & 4), a dummy variable indicating the rating downgrade during a firm-quarter (columns 2 & 5), and a dummy variable indicating the issuance of negative watch during a firm-quarter (columns 3 & 6). Variable definitions are in Appendix A. Standard errors of the coefficient estimates are clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Difference in firm characteristics between fraud and matched non-fraud firms

		Fraud firm		Non-fraud firm		Difference	
		Mean	Median	Mean	Median	Mean (t-stat)	Median (z-stat)
Matched sample 1 (208 matches)	*PM*	0.167	0.155	0.174	0.154	-0.50	0.50
	INTCOV	15.004	4.797	13.878	4.651	1.12	1.04
	LEV	0.334	0.323	0.345	0.317	-0.66	0.60
	SIZE	8.186	8.061	8.309	8.310	-0.86	-0.96
	RETVOL	0.027	0.024	0.026	0.022	1.06	1.30
	BETA	1.027	0.979	0.945	0.872	1.44	1.53
Matched sample 2 (170 matches)	Δ*PM*	0.009	-0.003	0.010	-0.002	-0.07	-0.28
	Δ*INTCOV*	-3.727	-0.422	-3.199	-0.287	-0.22	0.8
	Δ*LEV*	0.036	0.024	0.037	0.017	-0.12	0.37
	Δ*SIZE*	0.237	0.126	0.269	0.128	-0.58	-0.68
	Δ*RETVOL*	0.007	0.002	0.006	0.001	0.59	1.20
	Δ*BETA*	0.134	0.121	0.165	0.140	-0.51	-0.65
Matched sample 3 (2111 matches)	*PM*	0.177	0.158	0.168	0.155	1.65*	1.26
	INTCOV	12.396	4.608	11.429	5.130	1.25	-1.47
	LEV	0.362	0.363	0.363	0.342	-0.11	1.39
	SIZE	8.382	8.245	8.323	8.247	1.26	-1.23
	RETVOL	0.027	0.024	0.027	0.023	0.71	1.16
	BETA	0.982	0.933	0.952	0.912	1.11	1.30
	RETURN	-0.018	-0.022	-0.027	-0.022	1.39	0.57

Panel B: Regressions for the difference in rating actions between fraud and non-fraud firms, matched on industry and firm characteristics in the year prior to the start of the class period

Dependent Variables:	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)
	(1)	(2)	(3)	(4)	(5)	(6)
*Qtr_prior-8*FRAUD*	-0.061	-0.179	-0.641	-0.056	-0.024	-0.627*
	(-0.35)	(-0.87)	(-1.48)	(-0.31)	(-0.12)	(-1.74)
Qtr -8 FRAUD*	-0.052	0.187	0.332	-0.063	0.254	0.400**
	(-0.34)	(0.92)	(1.32)	(-0.39)	(1.24)	(2.01)
Qtr -7 FRAUD*	-0.050	0.009	0.320	-0.083	0.043	0.350
	(-0.34)	(0.02)	(1.22)	(-0.54)	(0.11)	(0.67)
Qtr -6 FRAUD*	-0.086	-0.225	-0.509	-0.070	-0.212	-0.828*
	(-0.67)	(-0.83)	(-1.38)	(-0.51)	(-0.73)	(-1.87)
Qtr -5 FRAUD*	-0.089	0.157	0.236	-0.107	0.097	0.142
	(-0.75)	(0.67)	(0.83)	(-0.87)	(0.38)	(0.47)
Qtr -4* FRAUD	**-0.149***	**0.482****	**0.561****	**-0.203***	**0.450****	**0.608*****
	(-1.87)	**(2.34)**	**(2.33)**	**(-1.94)**	**(2.04)**	**(2.64)**
Qtr -3* FRAUD	**-0.156****	0.138	**0.406****	**-0.216****	0.263	**0.367****
	(-1.96)	(0.64)	**(2.00)**	**(-2.24)**	(1.34)	**(1.98)**
Qtr -2* FRAUD	**-0.226****	**0.342****	**0.466****	**-0.274*****	**0.329****	**0.514****
	(-2.49)	**(2.07)**	**(2.11)**	**(-2.77)**	**(1.96)**	**(2.19)**
Qtr -1* FRAUD	**-0.320*****	**0.546*****	**0.627*****	**-0.363*****	**0.552*****	**0.600*****
	(-2.80)	**(2.78)**	**(2.60)**	**(-2.93)**	**(2.80)**	**(2.58)**
Qtr 0* FRAUD	**-0.397*****	**0.689*****	**0.975*****	**-0.425*****	**0.611*****	**1.012*****
	(-3.00)	**(3.83)**	**(4.86)**	**(-3.12)**	**(3.23)**	**(4.61)**
Qtr_prior-8	0.009	-0.095	0.288*	0.027	-0.236	0.212*
	(0.08)	(-0.64)	(1.94)	(0.24)	(-1.58)	(1.76)
Qtr -8	-0.047	-0.645	-0.385	-0.069	-0.604	-0.386
	(-0.47)	(-1.48)	(-1.04)	(-0.66)	(-1.34)	(-1.13)
Qtr -7	-0.069	-0.299	-0.535	-0.080	-0.261	-0.534
	(-0.66)	(-1.05)	(-1.22)	(-0.73)	(-0.88)	(-1.20)
Qtr -6	-0.034	0.112	0.200	-0.030	0.066	0.224
	(-0.39)	(0.55)	(0.93)	(-0.32)	(0.31)	(1.01)
Qtr -5	0.001	0.007	-0.010	-0.012	0.061	0.052
	(0.01)	(0.04)	(-0.04)	(-0.13)	(0.33)	(0.21)
Qtr -4	0.070	-0.210	-0.175	0.074	-0.191	-0.219
	(1.02)	(-1.27)	(-0.88)	(0.99)	(-1.07)	(-1.00)
Qtr -3	0.068	-0.015	0.023	0.082	-0.117	0.063
	(0.97)	(-0.08)	(0.11)	(1.10)	(-0.64)	(0.30)
Qtr -2	0.079	0.040	0.029	0.107	-0.014	-0.001
	(1.06)	(0.24)	(0.16)	(1.36)	(-0.08)	(-0.01)
Qtr -1	0.090	0.006	0.257	0.121	0.030	0.202
	(1.19)	(0.03)	(1.25)	(1.47)	(0.16)	(1.06)
Qtr 0	0.104	0.147	0.148	0.138	0.195	0.064
	(1.29)	(0.87)	(0.79)	(1.59)	(1.10)	(0.31)
Control for *ABSI*	No	No	No	YES	YES	YES
Other firm Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
#Firm-quarters	4,896	4,896	4,526	4,315	4,280	3,959
Pseudo R^2	0.28	0.19	0.14	0.29	0.20	0.15

Panel C: Regressions for the difference in rating actions between fraud and non-fraud firms, matched on industry and changes in economic performance during two years prior to the end of the class period

Dependent Variables:	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Qtr -8 FRAUD*	-0.105	0.168	-0.081	-0.109	0.185	-0.044
	(-1.36)	(0.64)	(-0.28)	(-1.38)	(0.75)	(-0.14)
Qtr -7 FRAUD*	-0.109	0.081	0.255	-0.115	0.106	0.041
	(-1.37)	(0.28)	(0.93)	(-1.40)	(0.33)	(0.14)
Qtr -6 FRAUD*	-0.201	-0.180	-0.189	-0.200	-0.156	-0.356
	(-1.54)	(-0.65)	(-0.57)	(-1.51)	(-0.55)	(-0.93)
Qtr -5 FRAUD*	**-0.304*****	0.194	0.108	**-0.355*****	0.272	0.094
	(-2.85)	(0.83)	(0.40)	**(-3.10)**	(1.05)	(0.32)
Qtr -4* FRAUD	**-0.397*****	**0.782*****	**0.314****	**-0.417*****	**0.768****	**0.363****
	(-3.56)	**(3.02)**	**(2.15)**	**(-3.55)**	**(2.56)**	**(2.44)**
Qtr -3* FRAUD	**-0.481*****	0.273	**0.366****	**-0.419*****	0.207	**0.400****
	(-4.09)	(1.13)	**(2.46)**	**(-3.44)**	(0.82)	**(2.54)**
Qtr -2* FRAUD	**-0.505*****	**0.448****	**0.434*****	**-0.461*****	**0.435****	**0.479****
	(-4.57)	**(2.08)**	**(2.94)**	**(-3.84)**	**(2.01)**	**(3.04)**
Qtr -1* FRAUD	**-0.497*****	**0.542*****	**0.535*****	**-0.450*****	**0.523*****	**0.661*****
	(-4.03)	**(2.85)**	**(3.35)**	**(-3.19)**	**(2.64)**	**(3.65)**
Qtr 0* FRAUD	**-0.639*****	**0.679*****	**0.938*****	**-0.565*****	**0.652*****	**1.091*****
	(-4.75)	**(3.36)**	**(4.59)**	**(-3.88)**	**(3.27)**	**(4.59)**
Qtr -8	0.034	-0.220	0.271	0.036	-0.101	0.221
	(0.55)	(-0.77)	(1.09)	(0.50)	(-0.35)	(0.85)
Qtr -7	0.072	-0.002	0.290	0.097	-0.023	0.352
	(1.07)	(-0.01)	(1.07)	(1.25)	(-0.08)	(1.28)
Qtr -6	-0.008	0.163	0.282	0.049	0.235	0.254
	(-0.11)	(0.68)	(0.97)	(0.65)	(0.93)	(0.80)
Qtr -5	0.003	0.290	0.392	0.032	0.232	0.342
	(0.03)	(1.20)	(1.45)	(0.38)	(0.90)	(1.20)
Qtr -4	0.011	-0.206	0.240	0.030	-0.196	0.106
	(0.13)	(-0.77)	(0.85)	(0.33)	(-0.65)	(0.33)
Qtr -3	0.043	0.086	0.411	0.019	0.234	0.404
	(0.50)	(0.35)	(1.55)	(0.21)	(0.94)	(1.47)
Qtr -2	0.066	0.179	0.378	0.056	0.112	0.131
	(0.81)	(0.81)	(1.45)	(0.61)	(0.45)	(0.44)
Qtr -1	-0.003	0.346	0.208	-0.013	0.436*	0.097
	(-0.03)	(1.51)	(0.80)	(-0.13)	(1.79)	(0.34)
Qtr 0	-0.024	0.296	0.431*	-0.007	0.323	0.207
	(-0.27)	(1.26)	(1.73)	(-0.06)	(1.27)	(0.73)
Control for *ABSI*	No	No	No	YES	YES	YES
Other firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
#Firm-quarters	3,019	3,019	2,780	2,517	2,444	2,258
Pseudo R^2	0.28	0.22	0.15	0.27	0.21	0.14

Panel D: Regressions for the difference in rating actions between fraud and non-fraud firms, matched on industry and lagged firm-quarter economic performance and stock return for each firm-quarter during two years prior to the end of the class period

Dependent Variables:	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)	*RATE*	Prob (*DG*=1)	Prob (*NW*=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Qtr -8 * *FRAUD*	-0.031	0.094	0.090	-0.152	0.522	0.263
	(-0.35)	(0.39)	(0.35)	(-1.41)	(1.54)	(0.92)
Qtr -7 * *FRAUD*	-0.077	0.042	0.394	-0.115	0.075	0.231
	(-0.79)	(0.18)	(1.58)	(-1.15)	(0.29)	(0.81)
Qtr -6 * *FRAUD*	-0.178*	0.014	-0.058	-0.129	0.017	-0.150
	(-1.87)	(0.05)	(-0.21)	(-1.17)	(0.06)	(-0.41)
Qtr -5 * *FRAUD*	-0.272***	0.415*	0.101	-0.297**	0.280	0.095
	(-2.60)	(1.91)	(0.43)	(-2.43)	(1.19)	(0.35)
Qtr -4 * *FRAUD*	-0.260***	0.615***	0.826***	-0.333***	0.445**	0.686**
	(-2.94)	(2.93)	(3.11)	(-3.37)	(2.01)	(2.47)
Qtr -3 * *FRAUD*	-0.326***	0.470**	0.224	-0.336***	0.516**	0.335
	(-3.47)	(2.13)	(1.10)	(-3.08)	(2.14)	(1.45)
Qtr -2 * *FRAUD*	-0.244***	0.668***	0.448**	-0.222**	0.525**	0.456**
	(-2.65)	(3.26)	(2.21)	(-2.12)	(2.30)	(2.26)
Qtr -1 * *FRAUD*	-0.153	0.341**	0.514***	-0.164	0.313*	0.650**
	(-1.41)	(2.05)	(2.65)	(-1.32)	(1.71)	(2.55)
Qtr 0 * *FRAUD*	-0.411***	0.828***	0.982***	-0.429***	0.801***	1.070***
	(-3.50)	(5.12)	(5.38)	(-3.24)	(4.17)	(5.14)
Qtr -8	0.085	-0.350	0.244	0.037	-0.515*	0.124
	(0.99)	(-1.38)	(0.99)	(0.38)	(-1.68)	(0.44)
Qtr -7	-0.073	-0.010	0.167	-0.010	-0.021	0.155
	(-0.86)	(-0.05)	(0.72)	(-0.11)	(-0.09)	(0.63)
Qtr -6	0.139	-0.071	0.191	0.187	-0.155	-0.008
	(1.41)	(-0.34)	(0.76)	(1.61)	(-0.62)	(-0.03)
Qtr -5	-0.115	-0.232	0.354	-0.071	-0.135	0.230
	(-1.32)	(-1.11)	(1.48)	(-0.71)	(-0.62)	(0.88)
Qtr -4	0.061	-0.233	-0.077	0.090	-0.056	-0.036
	(0.71)	(-1.13)	(-0.27)	(0.92)	(-0.26)	(-0.12)
Qtr -3	0.105	-0.233	0.482**	0.122	-0.329	0.339
	(1.18)	(-1.10)	(2.11)	(1.16)	(-1.27)	(1.35)
Qtr -2	0.040	-0.143	0.379	0.078	-0.077	0.301
	(0.46)	(-0.69)	(1.62)	(0.75)	(-0.34)	(1.18)
Qtr -1	-0.097	0.316*	0.430*	-0.062	0.332*	0.080
	(-1.01)	(1.76)	(1.89)	(-0.58)	(1.71)	(0.28)
Qtr 0	-0.006	0.145	0.505**	0.045	0.101	0.301
	(-0.07)	(0.80)	(2.23)	(0.41)	(0.50)	(1.18)
Control for *ABSI*	No	No	No	YES	YES	YES
Other firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
#Firm-quarters	4,222	4,222	4,092	3,234	3,234	2,888
Pseudo R^2	0.28	0.21	0.15	0.28	0.21	0.14

Table 5: Negative Rating Actions Conditional on Default Probability (EDF)

This table presents the frequency of negative rating actions, conditional on the commitment of accounting fraud and the level of default probability, based on fraud and matched non-fraud firms. Each panel groups a firm-year (firm-quarter) into four cells based on a two-way classification: (1) whether the firm-year (firm-quarter) involves accounting fraud and (2) whether the firm-year (firm-quarter) experiences a high or low level of default probability. For each matched sample, we first calculate firm-year (firm-quarter) EDF for both fraud and matched non-fraud firms during the corresponding class period. Next, we rank and partition all the firm-years (firm-quarters) into two groups based on the median value of EDF in that sample. Panel A presents the results for the sample where fraud and non-fraud firms are matched on industry and pre-fraud economic status. Panel B presents the results for the sample where fraud and non-fraud firms are matched on industry and changes in economic status during two years prior to fraud revelation. Panel C presents the results for the sample where fraud and non-fraud firms are matched on industry and firm-quarter economic status and stock returns during two years prior to fraud revelation. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: fraud and non-fraud firms matched on industry and firm characteristics in the year prior to the start of the class period

		High EDF	Low EDF	**Difference**
Fraud Sample	#firm-year	304	270	
	#DG&NW	125	48	
	%DG&NW	**41%**	**18%**	***23%****
Non-fraud Sample	#firm-year	259	293	
	#DG&NW	80	37	
	%DG&NW	**31%**	**13%**	***18%****
	Difference	***10%***	***5%**	

Panel B: fraud and non-fraud firms matched on industry and changes in economic performance during two years prior to the end of the class period

		High EDF	Low EDF	**Difference**
Fraud Sample	#firm-year	262	219	
	#DG&NW	97	41	
	%DG&NW	37%	19%	***18%****
Non-fraud Sample	#firm-year	219	261	
	#DG&NW	61	25	
	%DG&NW	28%	10%	***18%****
	Difference	***9%***	***9%****	

Panel C: fraud and non-fraud firms, matched on industry and firm-quarter economic performance and stock return for each firm-quarter during two years prior to the end of the class period

		High EDF	Low EDF	**Difference**
Fraud Sample	#firm-quarters	965	957	
	#DG&NW	198	76	
	%DG&NW	21%	8%	***13%****
Non-fraud Sample	#firm-quarters	957	965	
	#DG&NW	99	37	
	%DG&NW	10%	4%	***6%****
	Difference	***11%****	***4%****	

Table 6: Determinants of Rating Actions before Fraud Revelation

This table examines the determinants of the timeliness of S&P taking a negative rating action against fraud firms prior to fraud revelation. We estimate the Ordered Probit regressions. Variable definitions are in Appendix A. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables			*TIME*		
	Misstated Accounts	Fraud Severity	Information environment	Rating Industry Competition	Overall Effects
	(1)	(2)	(3)	(4)	(5)
REVENUE	0.036				0.448
	(0.18)				(1.40)
IV	0.398				0.499
	(1.52)				(1.31)
AR	0.290				0.319
	(1.31)				(0.98)
PPE	**0.470****				**0.862****
	(2.46)				**(2.14)**
INTANGIBLE	**0.394****				**0.969****
	(2.28)				**(2.32)**
EXPENSE	-0.137				-0.285
	(-1.05)				(-0.78)
LIABILITIES	**0.361****				**0.715****
	(2.18)				**(2.04)**
MA	-0.486				-0.629
	(-1.39)				(-1.52)
DURATION		**0.040****			**0.073*****
		(2.08)			**(3.03)**
SETTLE		**0.116****			**0.166***
		(1.97)			**(1.72)**
#MIS_ACCT		0.031			-0.210
		(0.53)			(-1.08)
#ANALYSTS			0.117		0.115
			(1.41)		(1.29)
ABSI			**2.518****		**1.496****
			(2.10)		**(2.12)**
LOAN			0.090		-0.132
			(0.37)		(-0.49)
CDS			-0.198		-0.111
			(-0.68)		(-0.36)
FITCH				-0.793	0.944
				(-0.39)	(0.35)
INTCOV	-0.010	-0.010	-0.002	-0.009	-0.010

	(-1.48)	(-1.54)	(-0.26)	(-1.38)	(-1.23)
PM	-2.347***	-2.015***	-2.971***	-1.989***	-3.943***
	(-3.17)	(-2.79)	(-3.51)	(-2.76)	(-4.16)
LEV	2.016***	2.194***	2.528***	2.226***	2.354***
	(2.93)	(3.22)	(3.16)	(3.30)	(2.81)
SIZE	0.110	0.102	0.160*	0.119	0.101
	(1.38)	(1.35)	(1.90)	(1.59)	(1.09)
DEBT/EBITDA	0.008	0.003	0.006	0.004	0.014
	(0.83)	(0.31)	(0.44)	(0.39)	(0.85)
EARNVOL	-0.475	-0.345	-0.865	-0.402	-0.681
	(-0.97)	(-0.71)	(-1.56)	(-0.84)	(-1.09)
CASH	0.386	-0.260	-0.425	0.117	-1.005
	(0.37)	(-0.24)	(-0.35)	(0.11)	(-0.73)
TANG	0.800	0.530	0.386	0.584	0.333
	(1.17)	(0.82)	(0.55)	(0.91)	(0.42)
CAPEX	0.029	0.720	3.450	0.203	3.369
	(0.02)	(0.43)	(1.57)	(0.12)	(1.48)
TOBINQ	-0.347**	-0.377***	-0.450***	-0.395***	-0.293
	(-2.44)	(-2.68)	(-2.67)	(-2.82)	(-1.62)
RE	0.906**	0.912**	0.814*	1.030**	0.723
	(2.18)	(2.18)	(1.82)	(2.54)	(1.52)
BETA	0.312	0.369	0.479*	0.345	0.491
	(1.31)	(1.57)	(1.75)	(1.48)	(1.64)
RETVOL	9.616	10.683	0.794	12.953	-0.564
	(0.88)	(0.97)	(0.06)	(1.19)	(-0.04)
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
#Events	259	259	228	259	228
Pseudo R^2	0.16	0.16	0.18	0.14	0.21

Table 7: Market Reactions to Rating Actions

This table compares market reactions to rating downgrades and negative credit watches between fraud and matched non-fraud firms prior to fraud revelation. Panel A presents the univariate analysis and Panel B presents the regression analysis. Variable definitions are in Appendix A. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Descriptive statistics

	Fraud Sample		Non-fraud Sample		Difference	
	Mean	Median	Mean	Median	Mean(t-stat)	Median(z-stat)
			Sample of rating downgrades (N=130 pairs)			
ΔRATE	-1.462	-1.000	-1.415	-1.000	-0.49	-0.44
LAG_RATE	10.208	10.000	10.185	10.000	0.05	0.48
CAR[-1,1]	-0.056	-0.019	-0.011	-0.014	-1.90*	-0.21
			Sample of negative credit watch additions (N=93 pairs)			
LAG_RATE	10.161	10.000	10.247	10.000	-0.18	-0.11
CAR[-1,1]	-0.087	-0.037	-0.010	-0.013	-2.38**	-2.16**

Panel B: Regression analysis

	Dependent Variables = *CAR[-1,1]*	
	Downgrade	Negative watch
	(1)	(2)
ΔRATE	**0.115****	
	(2.55)	
FRAUD	-0.059	**-0.076****
	(-1.19)	**(-2.37)**
*ΔRATE*FRAUD*	-0.010	
	(-0.33)	
LAG_RATE	-0.011	0.005
	(-1.42)	(0.95)
*ΔRATE*LAG_RATE*	-0.010**	
	(-2.13)	
Intercept	0.128	-0.059
	(1.55)	(-1.05)
# of Observations	260	186
Adj R^2	0.05	0.03

Table 8: Do Rating Actions Facilitate the Exposure of Accounting Frauds? - Survival Analysis

This table reports the coefficients estimates for the following parametric survival model: $log(M_i) = \beta' X_i + \varepsilon_i M_i$ is the quarter in which firm i's fraud is revealed to the public. The regression is estimated using data from all quarters in the class period through the quarter of the public revelation. X_i includes variables that are likely to affect the exposure of the fraud, including ratings (column 1 and 5), abnormal ratings (columns 2 and 6), a dummy variable indicating rating downgrade (columns 3 and 7), and a dummy variable indicating the issuance of negative watch (columns 4 and 8). Standard errors of the coefficient estimates are clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RATE	**0.058*****				**0.061****			
	(2.75)				**(2.34)**			
ABR		**0.089*****				**0.104*****		
		(4.12)				**(4.21)**		
DG			**-0.279*****				**-0.242****	
			(-3.01)				**(-2.29)**	
NW				**-0.476*****				**-0.484*****
				(-5.24)				**(-4.66)**
ABSI					-0.625**	-0.806***	-0.532**	-0.494**
					(-2.15)	(2.57)	(-2.29)	(1.97)
ABRET	0.680***	0.657***	0.678***	0.713***	0.676***	0.625***	0.716***	0.750***
	(4.56)	(4.15)	(4.27)	(4.61)	(3.40)	(3.11)	(3.56)	(3.78)
SIZE	-0.034	0.040	0.027	0.022	-0.022	0.057	0.041	0.037
	(-0.77)	(1.01)	(0.69)	(0.57)	(-0.41)	(1.24)	(0.89)	(0.80)
TOBINQ	-0.087*	-0.032	-0.055	-0.053	-0.087	-0.018	-0.044	-0.044
	(-1.71)	(-0.63)	(-1.02)	(-1.02)	(-1.27)	(-0.29)	(-0.64)	(-0.65)
LEV	-0.276	-0.343	-0.439	-0.504*	-0.287	-0.366	-0.479	-0.513
	(-0.92)	(-1.14)	(-1.45)	(-1.74)	(-0.80)	(-1.06)	(-1.36)	(-1.54)
PM	0.235	0.185	0.273	0.236	0.274	0.261	0.347	0.239
	(0.67)	(0.50)	(0.72)	(0.63)	(0.57)	(0.55)	(0.68)	(0.47)
RETVOL	3.642	-0.172	0.207	-0.710	3.225	-0.552	0.174	-0.568
	(0.74)	(-0.04)	(0.04)	(-0.16)	(0.55)	(-0.10)	(0.03)	(-0.10)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of firm-quarters	1,806	1,775	1,793	1,806	1,556	1,536	1,549	1,556