ABSTRACT: This study empirically tests whether the credit Watchlist creates an implicit contract between debt issuing firms and credit rating agencies (CRAs), whereby the CRA effectively motivates the issuer to take necessary actions that alleviate conditions that might otherwise lower the credit rating and then effectively monitors those actions. Based on Boot Milbourn, and Schmeits (2006), I hypothesize and provide evidence that, in response to negative economic news, issuers most likely to effectively respond to the terms of the implicit contract appear on the Watchlist. In addition, I find that firms placed on Watchlists generally manage earnings upward in both the year before and the year of the CRA announcement that the firm is “on watch.” I investigate various forms of earnings management, including accruals and real operating activities manipulation. Some evidence suggests that firms manage earnings in attempts to gain favorable Watchlist treatment. However, I find no evidence that the CRA is fooled by these attempts. Rather, it appears more likely that interpretation of other information or firm characteristics that make positive (negative) Watchlist firms poor candidates for credit upgrades (confirmations) guides CRA decisions and the CRA effectively “sees through” earnings manipulation aimed at managing CRA perceptions.

Keywords: Watchlist; credit risk; earnings management; credit analyst efficiency.

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I. Introduction

An important role of credit rating agencies (CRAs) arises from their credit watch procedure which creates an implicit contract between them and firms placed on the Watchlist. The credit watch procedure operates as follows: When a CRA observes potential changes in firm characteristics, it notifies management and asks for clarification, placing the firm “on watch.”¹ The CRA then asks the firm to provide information on how it plans to deal with potential increases in credit risk. The firm thus implicitly contracts to make a recovery effort to mitigate potentially adverse consequences of a credit rating change.

My study provides empirical evidence to address two aspects of the credit watch process. First, I conduct tests of the theoretical predictions in Boot, Milbourn, and Schmeits (BMS 2006), that the credit Watchlist provides effective monitoring and motivation for issuers and thus protects bondholders by alleviating conditions that might otherwise lower credit ratings. Second, I investigate whether firms engage in earnings management behavior that attempts to manipulate CRA perceptions during the Watchlist process and, if so, whether earnings management behavior appears to influence CRAs decisions.

Whether the Watchlist provides effective monitoring and motivation for issuers and thus protects bondholders is an important issue, particularly given the spotlight on CRAs in the wake of the recent worldwide credit crisis. CRAs play a significant role in the workings of financial markets by mitigating information asymmetry among lenders, investors, and issuers with regard to the creditworthiness of companies. One stream of the credit ratings literature examines the incremental value relevance of the credit watch procedure to financial markets. Hand et al. (1992) find that bond and stock prices change when CRAs add firms to the Watchlist, and Holthausen and Leftwich

¹ Keenan et al. (1998) indicate that credit watch is different from “rating outlook.” The outlook feature is an ongoing feature of all-long-term ratings. A change in rating outlook signals neither a rating change nor a review for potential change.
(1986) find that stock prices respond less to downgrades on firms that come off credit watch than firms downgraded without going on credit watch.

BMS argue that credit ratings serve as “focal points” that create desired equilibrium conditions in environments where multiple equilibria would otherwise exist. Essentially, credit ratings ensure against uncoordinated jumps to unfavorable equilibria. BMS argue further that the roles of CRAs as focal points occur most powerfully through the credit watch procedure where CRAs function as belief coordinators and monitors in the sense that institutional investors, for example, base their decisions on the observed ratings. Downgrades following a negative watch signal failure of the recovery efforts, and confirmations signal success.2 The BMS theory predicts that CRAs contribute most as monitors when, in the wake of negative news, they place firms with intermediate grade credit ratings on the negative Watchlist.3 To test this BMS proposition, I employ a logit model on a sample of issuers for the 27-year period beginning in 1981 and ending in 2007. Empirical evidence from the logit model is consistent with the BMS proposition and therefore supports their “focal point” theory about the credit watch procedure and, in particular, the effectiveness of the signaling role of the ratings that emerges from the credit watch procedure for intermediate versus high or low credit grade firms. 4

The second aspect of the credit watch process that I investigate relates to whether firms engage in earnings management through the manipulation of accruals and/or real operating activities surrounding the credit watch event and also whether CRAs’ rating changes reflect adjustments for earnings management. Examining the potential influence of earnings management on credit ratings

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2 Confirmation refers to where a firm comes off the Watchlist without a rating change.
3 BMS argue that moral hazard problems are small for firms with high credit ratings and the implicit contract associated with the credit watch has little incremental value, whereas, moral hazard problems are severe and no amount of monitoring significantly improves the probability of success for firms with low credit ratings.
4 If empirical evidence is not consistent with the BMS proposition, the possible explanation for the inconsistency will be either that the BMS assumptions are incomplete, my research design is flawed, or both.
is important because 42 percent of bonds issued by S&P 500 companies contain rating triggers\(^5\) (Bhanot and Mello 2006) and the operation of those triggers can precipitate liquidity crises, sharp declines in investor confidence, default, or bankruptcy (Frost 2007). Thus, CRAs play a fundamental monitoring role with respect to covenants contained in debt contracts. Because of the adverse consequences of rating triggers and the increased cost of debt resulting from lower ratings, firms have incentives to manage earnings upwards in an effort to obtain favorable ratings.

Recent research on the effects of earnings management on credit ratings addresses the question of whether firms manage earnings in order to obtain favorable ratings and, if so, whether CRAs make rating changes reflecting adjustments for earnings management; that is, whether managers successfully fool CRAs. The empirical evidence is mixed. Ali and Zhang (2008) and Jung et al. (2009) show increased earnings management activities (discretionary accruals or earnings smoothing) when firms are near a broad credit rating change. Jung et al. (2009) conclude that increased earnings smoothness improves the likelihood of favorable rating changes. In contrast, other studies provide evidence that CRAs make rating changes reflecting adjustments for earnings management (Caton et al. 2006; Jorion et al. 2009). While many studies examine whether managers employ discretionary accruals as a tool to manage earnings in order to obtain favorable ratings, those studies do not consider manipulation of real operating activities to manage earnings and CRA perceptions, and I have not seen any studies that examine earnings management behavior in the context of the credit watch process.

To address whether firms on the negative (positive) Watchlist with later downgrades (rating confirmations) are more likely to manage earnings upward than are firms on the same Watchlist with rating confirmations (later upgrades), my research design includes two steps. I compute the difference in both accrual-based and real earnings management measures in the year of placement.

\(^5\) A rating trigger is a contractual provision that gives the lender specified rights when a borrower’s credit ratings decline to a certain level (Stumpp 2001).
on the Watchlist and the immediately preceding year for each group. Then I test the difference between the two groups.

This study makes two contributions to the extant literature on credit ratings quality and earnings management. First, it provides evidence on the BMS focal point theory; in particular, the signaling effects of the credit watch procedure. Second, this study extends the literature on the effects of earnings management on credit ratings by documenting earnings management activities when firms are placed on credit watch. 6 The study investigates earnings management both through manipulation of accruals and manipulation of real operating activities, following Graham et al. (2005) who provide survey evidence describing managers’ preferences for earnings management through manipulation of real operating activities. I suspect that the cash component of earnings is especially important in the context of credit rating changes, and managers might prefer (or find it necessary) to manipulate real operating activities in this context.

My analyses provide evidence supporting the following two important inferences. First, the study provides evidence consistent with the BMS proposition that firms with intermediate grade ratings are more likely than other firms to appear on the Watchlist in response to negative economic news. These results support the BMS “focal point” theory and, in particular, the signaling effects of the credit watch procedure. In addition, I document that firms generally engage in upward earnings management in both the year prior to and the year of placement on the Watchlist. However, assuming that these results reflect managers’ attempts to gain favorable treatment during the Watchlist process, I find no evidence that the CRA is fooled. For example, I document that firms on the positive Watchlist with later rating confirmations are more likely to manage earnings upward, through manipulation of discretionary expenses, than are firms on the same Watchlist with later

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6 Ball and Shivkumar (2008) suggest that upward-biased estimates of discretionary accruals occur around large transactions and events such as initial public offerings. My study may be unaffected by such bias because the negative and positive Watchlists are unlikely to be systematically associated with large transactions and events. CRAs reserve the developing Watchlist designation for such events.
upgrades. This pattern suggests that credit analysts take rating actions that reflect adjustments for earnings management through manipulation of discretionary expenses. In fact, one interpretation of the evidence is that this earnings management behavior is associated with other firm characteristics that make positive (negative) Watchlist firms poor candidates for credit upgrades (confirmations), and the CRA observes these other firm characteristics and effectively “sees through” the earnings management, when making credit rating decisions.

The remainder of this paper is organized as follows: section II develops the hypotheses; section III develops the research design; section IV describes the samples; section V presents the results; and section VI concludes.

II. Research Questions and Hypotheses Development

This study investigates two research questions:

(1) Does empirical evidence pertaining to CRA decisions to place firms on the Watchlist conform to the proposition that firms with recent bad news and intermediate grade credit ratings benefit more from the implicit contracting and monitoring by CRAs and therefore are more likely to be placed on negative credit watch? BMS refers to this prediction as proposition #5.7

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7 BMS (2006) make five predictions drawn from their model. Proposition #1 hypothesizes that, if the likelihood of successful restorations of firms’ credit quality is higher, the magnitude of stock market reaction to publicly-observed bad news is less negative. Proposition #2 predicts a negative relation between the magnitude of market reactions after a credit watch and the magnitude of market reactions to the bad news. Proposition #3 predicts that market reactions to the credit watch announcements are conditional on market expectation for the likelihood of successful restorations of firms’ credit quality. Proposition #4 predicts the conditions under which the effectiveness of the CRA is limited. Proposition #5 links the credit quality to the likelihood of being on the Watchlist. Propositions #2, #3 and #5 are related to the credit watch procedure. In this paper, I focus on proposition #5 from the BMS theory as described in the text above.
(2) Do financial reports issued while a firm is on the Watchlist exhibit upward earnings management, reflecting management attempts to increase the odds of a favorable resolution? If so, are resolutions consistent with the notion that CRAs make rating changes that reflect adjustments for earnings management?

A. The Credit Watch as a Mechanism for Monitoring and Implicit Contracting

S&P (2008a) uses the credit watch procedure “when an event or deviation from an expected trend has occurred or is expected such that there is a significant chance (50% or more) of requiring a rating change, and additional information is necessary to take a rating action. Moody’s (Keenan et al. 1998) places issuers on the Watchlist in any of three scenarios:

1. The issuer has announced plans that Moody’s believes would materially affect credit quality, but that are not certain to come to fruition;
2. Trends in the issuer’s operations or financial strength, in its industry or regulatory regime, or in the macroeconomic fundamentals of its country of domicile or region of operation may develop that could affect—positively or negatively—the issuer’s willingness and ability to pay its debts on time; and
3. An event suddenly occurs that changes the issuer’s operating environment, but the magnitude of its effect on the issuer is not clear.

In addition, Moody’s indicates that the developing Watchlist is more likely connected to announced plans.

The sequence of events begins at the point in time (t = 0) when the firm announces that it will use debt financing to invest in a new project and the CRA sets an initial credit rating based on the anticipated project choice.\(^8\) In response to negative economic news, the CRA decides whether to initiate a credit watch procedure (t = 1). If the firm is placed on credit watch, the firm chooses whether to undertake recovery effort. After observing the recovery effort and its success or failure,

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\(^8\) A firm either chooses a viable project with moderate payoffs or a high risk project with high payoffs. Investment in a viable project is first-best efficient, no matter the firm’s credit quality.
the CRA assigns a new rating or confirms the old rating \( (t = 2) \). At time \( t = 3 \), the project’s payoff is realized, and the firm either repays its debt or defaults. I summarize the sequence of events in Figure 1. BMS argue that a rating downgrade following a credit watch provides particularly informative news to the market, because the downgrade indicates that the firm did not successfully complete the actions necessary to restore its credit quality and failed to fulfill the terms of the contract implicitly made with the CRA upon placement on credit watch. While downgrades following a negative watch signal failure of the recovery efforts, confirmations signal success.

BMS (2006 p. 106) further suggest that their model “speaks to the likelihood of a firm entering the credit watch procedure in response to negative economic news, as opposed to being directly downgraded.” Their analytical model predicts that the likelihood of being placed on the Watchlist is nonmonotonic in the distribution of credit quality. Specifically, Proposition #5 in the BMS paper predicts:

The likelihood of being put on credit watch is (i) very small for low quality firms since the credit watch procedure is unlikely to be effective, (ii) small for firms of very high quality as the credit watch procedure is redundant, and (iii) large for firms of intermediate quality for which the credit watch procedure is most valuable.

BMS’s model links the likelihood of being placed on the Watchlist after deteriorations in credit quality to the effectiveness of recovery efforts and firms’ initial credit quality. Because recovery efforts are costly, BMS conclude that the credit watch procedure adds most value for firms when

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9 Institutional investors base their investment decisions on the rating. White (2002) defines safety-and-soundness regulation as regulation banning the holding of securities that fall below a specified grade, or specifying capital requirements for holding the securities that are geared to their ratings.

10 Hirsch and Bannier (2009) try to distinguish two lines of argument for economic rationale behind credit watch: buying time vs. implicit contracting. Their findings suggest that the credit watch procedure lends support to BMS’s focal point theory: whereas direct rating downgrades make a statement on the issuers’ lack of capability or willingness to sustain their credit quality, Watchlist downgrades inform market participants of borrowers’ lack of success in doing so. The buying time argument suggests that Watchlists help alleviate rating instability and inaccuracy in that they allow CRAs to buy time for an eventual rating decision. The buying time argument suggests that credit analysts directly change a rating only if it is certain that the change in the issuers’ credit quality is strong and long-lasting.
the probability that the recovery efforts will be successful is within a certain range (Corollary to Theorem 4).\textsuperscript{11}

BMS argue that the recovery efforts of low credit quality (LCQ) firms always fail and therefore LCQ firms on average do not undertake recovery efforts in response to negative economic news. In other words, LCQ firms always choose high risk projects (undesirable equilibrium). Since the credit watch procedure is “unlikely to be effective” for LCQ firms, the likelihood of these firms being placed on the Watchlist is very small.

In the BMS model, high credit quality (HCQ) firms always undertake recovery efforts in response to deteriorations in credit quality and make great efforts to succeed regardless of credit watch procedures. HCQ firms may have even more incentives to keep their strong ratings because they have more to lose, and other monitors, such as equity analysts, may be available. This is not true for intermediate credit quality (ICQ) and/or LCQ firms. That is, HCQ firms on average can recover successfully without the CRA’s monitoring. In other words, HCQ firms always choose viable projects (desirable equilibrium). Therefore, it seems redundant to place HCQ firms on the Watchlist.

Investor beliefs about ICQ firms’ project choice and the effectiveness of their recovery efforts are divergent. Furthermore, multiple equilibria are possible since investor beliefs about an ICQ firm’s project choice are important in determining either a desirable or an undesirable equilibrium as indicated in BMS Theorem 1.\textsuperscript{12} In other words, the CRA’s coordination role (monitoring firms’

\textsuperscript{11} BMS Corollary to Theorem 4: A credit watch procedure increases the range of values of \( \beta \) for which the firm engages in recovery effort compared to the passive case with only beliefs-coordination by CRAs; all firms with \( \beta \geq \beta_c \), where \( \beta_c \) is the firm’s commitment to make recovery efforts. \( \beta \) refers to the probability that the recovery efforts will be successful.

\textsuperscript{12} BMS Theorem 1. The firm’s project choice in equilibrium depends on its credit quality \( p \). In particular, the following regions can be distinguished:

1. If \( p < p^* \), then the firm always chooses project HR (high risk), regardless of investors’ beliefs (anticipation) with respect to its project choice.
2. If \( p \leq p^* < p \), then the firm chooses whichever project investors anticipate will be taken. That is, if investors anticipate that the firm chooses the viable project VP, the firm optimally chooses VP. However, if investors anticipate HR, then it is optimal for the firm to choose HR. Hence, in this region there are multiple equilibria.
recovery efforts and thus coordinating investor beliefs) offers the most value for ICQ firms. Accordingly, relative to high or low quality firms, CRAs are most likely to place ICQ firms on the Watchlist because in this group the CRA monitoring role is most likely to influence the effectiveness of the firms’ recovery efforts.

My first hypothesis (in alternative form) is

\[ H_{1a}: \text{The inverse relation between news about a firm’s prospects and the likelihood of the CRA placing the firm on the negative (NEG) Watchlist is greater for firms with medium ratings as compared to firms with high or low ratings.} \]

\[ H_1 \] provides the basis for the empirical tests of proposition #5 of BMS. Empirical evidence consistent with proposition #5 would support the authors’ “focal point” theory about the credit watch procedure and, in particular, the theory’s explanation of the signaling effects of the credit watch procedure.

**B. Earnings Management and the Credit Watch Process: Do Managers Fool Credit Analysts?**

While the existing empirical evidence (Holthausen and Leftwich 1986; Hand et al. 1992) is consistent with the focal point theory, our findings consistent with \( H_{1a} \) support the economic value of the credit watch process to CRAs, playing an active role rather than a passive role. \(^{13}\) BMS’s model suggests that the credit watch process improves the ability of CRAs to solve moral hazard problems along two dimensions. \(^{14}\) First, the credit watch process induces some issuers to engage in recovery efforts from which they otherwise would have abstained, because the potential higher cost of debt makes recovery efforts more attractive to these issuers. Without the process, CRAs cannot observe whether firms engage in recovery efforts and thus cannot provide an advance signal to the

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3. if \( P \geq \tilde{P} \), then the firm chooses the viable project VP, regardless of investors’ beliefs with respect to its project choice.

13 Holthausen and Leftwich (1986) and Hand et al. (1992) provide evidence that investors benefit from an early warning of potential risk changes but do not provide evidence on the economic value of the credit watch procedure to CRAs.

14 Moral hazard problems refer to both issuers’ project choice and the success or failure of recovery efforts that are unknown to investors.
markets about forthcoming rating actions. In addition, to enforce good equilibrium, CRAs need a smaller proportion of institutional investors with the credit watch process than without it. In other words, the credit watch process makes it easier for Crass to coordinate investor beliefs about firms’ project choice. Since the credit watch procedure makes CRAs function more efficiently and thus facilitates investors’ investment decisions, it would be interesting to examine both the issuers’ behavior and CRAs’ behavior surrounding the Watchlist. This study focuses on issuers’ earnings management behavior and credit analysts’ rating actions related to such behavior in the context of the Watchlist.

Because of the adverse consequences of rating triggers and the increased cost of debt resulting from lower ratings, firms have incentives to manage earnings upwards so as to obtain favorable ratings.\textsuperscript{15} Since issuers know their own ‘true’ performance, and thus, credit risk, some issuers can predict when and whether they will be placed on the Watchlist in response to negative economic news. Markets do not share the same information set. Issuers thus have incentives to manage earnings preemptively to avoid being on the NEG Watchlist because markets will react negatively to unexpected NEG Watchlist placement. Issuers also have incentives to manage earnings in order to obtain a favorable rating resolution when they are on the Watchlist. After the credit watch period, some issuers will still have incentives to manage earnings for better ratings in the future. It is also plausible that issuers would be under continued scrutiny in the time period following the credit watch procedure, since being placed on the Watchlist is a signal that the markets use. The added scrutiny may be by both CRAs and the markets. In other words, issuers have incentives to obtain favorable ratings no matter whether it is before, during, or after the credit watch period, as long as they need new funding.\textsuperscript{16} I expect that the incentives to manage earnings during the credit watch

\textsuperscript{15} The debt covenant hypothesis predicts earnings management for covenant purpose (Watts and Zimmerman 1986).
\textsuperscript{16} If a firm has no need for new funding and its existing debt is unlikely to be repriced soon, the coordinating roles of CRAs are limited as suggested in BMS Footnote 23.
period are strongest because of implicit contracts between CRAs and issuers. It may seem that real earnings management over a short period is unlikely. Nonetheless, since issuers can predict CRAs’ behavior, these issuers could conduct real earnings management throughout the year they were placed on the Watchlist even if they were placed on the Watchlist only a few days.\textsuperscript{17}

Jorion et al. (2009) find that accounting quality, measured by discretionary accruals, may explain the downward trend of credit ratings for investment grade firms during 1985-2002. Jorion et al.’s findings underscore that accounting quality plays a critical role in the rating process. On the one hand, consistent with Jorion et al.'s findings, credit analysts may be able to make efficient adjustments for financial statements when assessing credit risk. In particular, credit analysts should be able to detect earnings management to a large degree. Furthermore, Smith and Walter (2002) conclude that rating agencies successfully manage built-in conflicts of interest with their customers and that agency conflicts are controlled.\textsuperscript{18} CRAs’ policy to manage conflicts of interest includes that they have fixed fee schedules, that analysts are not compensated based on the revenues associated with the companies that they rate, and that analysts are not permitted to hold or trade in the securities of issuers that they analyze.

On the other hand, a congressional hearing in Oct. 2008 held that major CRAs carry significant responsibility for the current financial crisis because of low rating quality. The low rating quality may have resulted from conflicts of interest (perceived and actual) arising from CRAs’ reliance on revenues from issuers.\textsuperscript{19} Revenues for the three firms (S&P, Moody’s, and Fitch) doubled from $3 billion in 2002 to over $6 billion in 2007. Moody’s profits quadrupled between 2000 and 2007, and the company reported the S&P 500's highest profit margin over a five-year period. CRA revenues

\textsuperscript{17} If my assumption that firms’ incentives to manage earnings are strongest during the Watchlist period is incorrect, then the power of my test to find earnings management during the Watchlist period is reduced.

\textsuperscript{18} Reputation is one important mechanism creating incentives for CRAs to provide investors with accurate ratings. In addition, although CRAs enjoy immunity from liability for misstatements made in registration statements, under section 11 of the Securities Act of 1933, pending lawsuits drive down the stock prices of CRAs’ parents (McGraw Hill Companies and Moody’s Corporation).

\textsuperscript{19} In this case, CRAs collude with management to “inflate” ratings.
include rating revenues and advising revenues. In addition to issuers paying CRAs for ratings, CRAs also make profits by advising issuers on how to structure mortgage-backed securities (MBSs) and Collateralized Debt Obligations (CDOs) in a manner likely to receive high ratings.\textsuperscript{20} Therefore, an interesting empirical question is whether firms managing earnings are able to influence CRAs’ rating decisions.

When a firm is placed on the NEG Watchlist, the firm must undertake a significant recovery effort to convince CRAs to assign a rating confirmation. Obviously, a firm with a rating confirmation has successfully persuaded CRAs that its credit risk has not changed, while a firm with a downgrade has not successfully done so. One conjecture is that some firms are downgraded because instead of making real recovery efforts, they manage earnings in an attempt to fool CRAs and the CRAs can detect this behavior.\textsuperscript{21} Another possibility is that firms with confirmations were successful in hiding their earnings management. Therefore, I allow for two possible outcomes from earnings management behavior. Firms obtain confirmations as a result of earnings management behavior that fool CRAs. Alternatively, CRAs detect earnings management and downgrade the ratings of firms engaging in that behavior. My second hypothesis (in alternative form) is

$$H_{2a}: \text{Ceteris paribus, the difference in earnings management between the year immediately prior to and the year of placement on the NEG Watchlist significantly differs between firms with later downgrades and firms with rating confirmations.}$$

\textsuperscript{20} In 2007 and prior years, Moody’s operated in two reportable segments: Moody’s Investors Service and Moody’s KMV. Beginning in January 2008, the rating agency remains in the MIS operating segment and all of Moody’s other non-rating commercial activities combined under a new operating segment known as Moody’s Analytics. The rating revenues were 1,204.7 million dollars while the consulting revenue was 25.6 million dollars in 2008 (Moody’s 2008 annual report).

\textsuperscript{21} The decision to manage earnings by issuers to obtain favorable credit ratings may be endogenous. Issuers with lower levels of ratings may have less ability to manage earnings while issuers with higher levels of ratings may face fewer incentives to manage earnings. In that case, I expect to find more earnings management by ICQ firms. However, my hypothesis focuses on firms that come off the Watchlist with ratings changes versus those coming off the Watchlist with confirmations and whether the CRA decision is associated with the firms’ earnings management behavior.
I use annual versus quarterly reports because annual reports may give users one year of financial information while quarterly reports provide financial information for a relatively short period. In general, annual reports are audited while quarterly reports are not.

A similar argument is applied to the two groups on the positive (POS) Watchlist: firms with later upgrades and firms with rating confirmations. Firms coming off the POS Watchlist with confirmations serve as a control group. My third hypothesis (in alternative form) is

\[ H_{3a}: \text{Ceteris paribus, the difference in earnings management between the year immediately prior to and the year of placement on the POS Watchlist differs significantly between firms with later upgrades and firms with rating confirmations.} \]

A finding that NEG Watchlist firms with more earnings management are more likely to receive downgrades (confirmations) would provide evidence consistent with the notion that CRAs take rating actions that reflect (do not reflect) adjustments for earnings management. A finding that POS Watchlist firms with more earnings management are more likely to receive confirmations (upgrades) would provide evidence consistent with the notion that CRAs take rating actions reflecting (not reflecting) adjustments for earnings management.\(^{22}\)

BMS suggest that the likelihood of successful restorations of credit quality for firms on the NEG Watchlist depends on factors including firms’ reputation and/or quality of management, cost structure, type of assets, and financial structure. It is possible that CRAs take actions not just to adjust for earnings management per se, but also to implicitly link the level of earnings management to the quality of management or other firm characteristics. In other words, CRAs may perceive the quality of management in firms with earnings management as low and thus assess that these firms may not be able to restore their credit quality. Accordingly, CRAs might downgrade (confirm)

\(^{22}\) If low quality firms have less ability to manage earnings, then this adds noise to my analysis which assumes all firms have room to manage earnings through manipulation of accruals or real activities.
rather than confirm (upgrade) their ratings, if the CRAs discover that firms have managed earnings upward when placed on the NEG (POS) Watchlist. On the other hand, if earnings management occurs but CRAs do not detect the behavior, they may misperceive the quality of the firm and confirm (upgrade) the ratings of firms that manage their earnings upwards while on the NEG (POS) Watchlist.

III. Research Design

A. Model to Test Hypothesis $H_1$

Direct measurement of economic news is problematic. I therefore employ an ex-ante proxy for economic news: cumulative abnormal returns (CAR) on stock over the 90 days prior to placement on the Watchlist or since the day prior to the most recent quarterly earnings announcement, whichever period is longer. Negative CARs serve as a proxy for negative economic news. Compared to rating downgrades as a proxy for negative economic news, the benefits associated with the use of negative CARs are that they represent an ex ante proxy, measure the magnitude of the news, and allow the sample to include observations of firms with negative news which were not ultimately downgraded. A limitation of the CAR proxy is that negative news to shareholders is not necessarily bad news to bondholders, and CAR proxies for public information available to the CRA, while the CRA bases the credit watch and rating change decision on both public and private information.

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23 CARs are market and risk-adjusted returns computed as the firm’s raw return minus the expected return based on the market model estimated over the 250 days prior to the abnormal return accumulation period. I considered using earnings surprise as a proxy for news but my final sample would only include relatively large firms due to the requirement of analysts’ forecasts and would not be representative.

24 The downgrade sample also excludes observations associated with negative economic news but ultimately not downgraded, that is, observations on the NEG Watchlist with later confirmations.
To test my hypothesis, I apply a logit model to data obtained from a sample of issuers. I focus on the NEG Watchlist because a bad signal suggests serious moral hazard problems. I assume that the marginal probability of being on the NEG Watchlist over the next period follows a logistic distribution and is given by

\[ P(Y_{ij} = 1) = \frac{1}{1 + \exp(-\alpha - \beta x_{ij})} , \]  

where \( Y_{ij} \) is an indicator that equals one if firm \( i \) is placed on the NEG Watchlist in month \( j \) and otherwise zero, and \( x_{ij} \) is a vector of explanatory variables.

I estimate a logistic regression with the explanatory variables: ICQ, NEWS, and NEWS*ICQ. ICQ (intermediate credit quality) is equal to one if the firm’s rating is between A+ and BB-; zero otherwise. NEWS is cumulative abnormal returns (CAR) multiplied by negative one, where CARs are computed as market and risk-adjusted stock returns over the 90 days prior to placement on the Watchlist or since the day prior to the most recent quarterly earnings announcement, whichever period is longer. The higher the value of NEWS, the more negative the news. The explanatory variable of interest is NEWS*ICQ. Based on BMS’s proposition #5, I expect the coefficient on NEWS*ICQ to be positive.

**B. Measurement of Earnings Management**

My tests employ multiple proxies for earnings management as follows:

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25 BMS (2006 p. 110) assume that CRAs will invoke credit watch procedures that are at times independent. They indicate that the rationale of their predictions do not depend on the number of rating agencies. They suggest that “the design of the empirical tests has to carefully take into account … multiple credit watch announcements. This, and the possibility of more or less tentative behavior of the rating agencies, will have a potential impact on the size of the announcement effects.” Since I only test Proposition #5 (the relationship between firms’ credit quality and the likelihood of being placed on credit watch), which does not involve announcement effects, I consider it unnecessary to control for multiple credit watch announcements.

26 I exclude observations on the NEG Watchlist with later upgrades because of the possibility of error in NEG Watchlist placement, and I calculate clustered standard errors to adjust for clustering on firms (Chamberlain 1980; Cameron and Trivedi 2005; Luce 1959; Maddala 1991; McFadden 1973; Peterson 2008).

27 The appendix provides descriptive evidence of a dramatic increase in credit loss rates between the B and C credit rating categories.

28 The coefficient on NEWS*ICQ is positive if the likelihood of the CRA placing the firm on watch increases (decreases) with prior bad (good) news. In either case, a significantly positive coefficient on the interaction term supports the BMS theory.
(1) Accrual-based Earnings Management

I use a cross-sectional model of discretionary accruals, where for each year I estimate the model for each industry classified by its two-digit SIC code. My primary model is the modified cross-sectional Jones model (Dechow et al. 1995; DeFond and Jiambalvo 1994; Jones 1991). The modified Jones model is estimated by industry as follows:

\[
\frac{TA_{it}}{Assets_{t-1}} = k_1 \frac{1}{Assets_{t-1}} + k_2 \frac{\Delta REV_{it}}{Assets_{t-1}} + k_3 \frac{PPE_{it}}{Assets_{t-1}} + \varepsilon_{it}
\]  

where, for fiscal year t and firm i, \( TA \) represents total accruals defined as (annual Compustat data code in the parentheses):

\[
TA_{it} = EBXI_{it} - CFO_{it}, \text{ where } EBXI \text{ is the earnings before extraordinary items and discontinued operations (IBC) and } CFO \text{ is the operating cash flows (from continuing operations) taken from the statement of cash flows (OANCF – XIDOC); }^{29}
\]

\[
\text{Assets}_{t-1} = \text{total assets (AT)};
\]

\[
\Delta REV_{it} = \text{change in revenues (SALE) from the preceding year}; \text{ and}
\]

\[
PPE_{it} = \text{gross value of property, plant, and equipment (PPEGT)}.
\]

The coefficient estimates from Equation (2) are used to estimate the fitted normal accruals \( (NA_{it}) \) for my sample firms:

\[
NA_{it} = \hat{k}_1 \frac{1}{Assets_{t-1}} + \hat{k}_2 \frac{\Delta REV_{it} - \Delta AR_{it}}{Assets_{t-1}} + \hat{k}_3 \frac{PPE_{it}}{Assets_{t-1}}
\]  

where \( \Delta AR_{it} \) is the change in accounts receivable (RECCH) from the preceding year.

I estimate the industry-specific regressions using the change in reported revenues, assuming no discretionary choices with respect to revenue recognition. Nonetheless, while computing the normal accruals, I adjust the reported revenues of the sample firms for changes in accounts receivable to

\[^{29}\text{Hribar and Collins (2002) identify measurement errors in accruals estimates using a balance sheet approach, particularly in the contexts of business combinations and discontinued operations. I use a cash flow statement approach rather than a balance sheet approach to compute total accruals. An alternative approach is to use a balance sheet approach but delete observations with significant changes in the nature or structure of the business entity.}\]

16
capture any potential accounting discretion arising from credit sales. My measure of discretionary accruals is the difference between total accruals and fitted normal accruals, defined as \( DA_{it} = (TA_{it} / Assets_{i,t-1}) - NA_{it} \). \(^{30}\)

(2) Earnings Management through Manipulation of Real Operating Activity

Based on Roychowdhury (2006) and Gunny (2009), I employ the abnormal levels of cash flows from operations (CFO), discretionary expenditures (DiscExp), and production costs (Proc) to measure the level of real activities manipulations. Following Cohen et al. (2008), I focus on three manipulation methods and their impact on the above three variables:

1. Acceleration of the timing of sales through increased price discounts or more lenient credit terms
2. Reporting of lower cost of goods sold through increased production
3. Decreases in discretionary expenditures that include advertising expense, research and development, and SG&A expenditures

To estimate the abnormal level of CFO, following Roychowdhury (2006) and Gunny (2009), I run the following cross-sectional regression for each industry and year:

\[
\frac{CFO_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{Sales_{it}}{Assets_{i,t-1}} + k_3 \frac{\Delta Sales_{it}}{Assets_{i,t-1}} + \varepsilon_{it} \tag{4}
\]

Abnormal CFO is actual CFO minus the normal level of CFO calculated using the estimated coefficient from Equation (4).

Production costs are defined as the sum of the cost of goods sold (COGS) and the change in inventory during the year (Roychowdhury 2006). \(^{31}\) I model COGS as a linear function of contemporaneous sales:

\[^{30}\text{I employ an alternative measure for discretionary accruals: performance-matched discretionary accruals (Kothari et al. 2005). I match each firm-year observation with another from the same two-digit SIC code and year with the closest returns on assets in the current year, ROA}, \text{net income divided by total assets). This approach controls for the effect of performance on measured discretionary accruals. As a sensitivity check, I extend the matching to include lagged ROA.}\]
\[
\frac{COGS_{it}}{Assets_{t-1}} = k_1 \frac{1}{Assets_{t-1}} + k_2 \frac{Sales_{it}}{Assets_{t-1}} + \varepsilon_{it}.
\]  

(5)

Next, I model inventory growth by the following:

\[
\frac{\Delta INV_{it}}{Assets_{t-1}} = k_1 \frac{1}{Assets_{t-1}} + k_2 \frac{\Delta Sales_{it}}{Assets_{t-1}} + k_3 \frac{\Delta Sales_{i,t-1}}{Assets_{t-1}} + \varepsilon_{it}.
\]  

(6)

Using Equations (5) and (6), I estimate the normal level of production costs as:

\[
\frac{Prod_{it}}{Assets_{t-1}} = k_1 \frac{1}{Assets_{t-1}} + k_2 \frac{Sales_{it}}{Assets_{t-1}} + k_3 \frac{\Delta Sales_{it}}{Assets_{t-1}} + k_4 \frac{\Delta Sales_{i,t-1}}{Assets_{t-1}} + \varepsilon_{it}.
\]  

(7)

I model the normal level of discretionary expenditures as:

\[
\frac{DiscExp_{it}}{Assets_{t-1}} = k_1 \frac{1}{Assets_{t-1}} + k_2 \frac{Sales_{it}}{Assets_{t-1}} + \varepsilon_{it}.
\]  

(8)

Cohen et al. (2008) indicate that modeling discretionary expenditure as a function of current sales creates a mechanical problem if firms manage sales upward to increase reported earnings in a certain year, resulting in significantly lower residuals when running a regression as derived in Equation (8). \textit{DiscExp} is defined as the sum of advertising expenses (XAD), R&D expenses (XRD), and SG&A (XSGA). \footnote{Examining production costs instead of COGS has two advantages. First, production costs primarily reflect the effects of real activities. Second, the LIFO/FIFO cost flow assumption affects COGS, but not production costs.}

Following Cohen et al. (2008), I estimate ‘normal’ levels of discretionary expenditures by the following model:

\[
\frac{DiscExp_{it}}{Assets_{t-1}} = k_1 \frac{1}{Assets_{t-1}} + k_2 \frac{Sales_{it}}{Assets_{t-1}} + \varepsilon_{it}.
\]  

(9)

\footnote{If XRD is missing, I code it as zero.}
The abnormal Prod and abnormal DiscExp are computed as the difference between the actual values and the normal levels predicted from Equations (7) and (9).

C. Tests of Earnings Management Hypotheses: H₂ and H₃

To test H₂, I identify two groups on the NEG Watchlist: the group of firms with later downgrades and the group of firms with rating confirmations. I compute the difference for earnings management measures between year \( t \) and year \( t-1 \) (\( DIFY \)) for each group and test the difference between the two groups. A difference-in-differences design accounts for unobserved differences between the group with later downgrades and the group with rating confirmations. The design also adjusts observed changes for one group by concurrent changes that are experienced by another group.

A similar approach is employed to test H₃. I identify two groups on the POS Watchlist: the group of firms with later upgrades and the group of firms with rating confirmations. I compute the difference for each earnings management measure between year \( t \) and year \( t-1 \) (\( DIFY \)) for each group and test the difference between the two groups.

IV. Sample and Descriptive Statistics

My empirical tests employ data from three sources:

1) Financial statement data – the COMPUSTAT fundamentals annual file
2) S&P Watchlist data – S&P Credit Ratings database
3) Stock returns – the CRSP daily stock returns files

A. The Watchlist Sample for Testing H₁

S&P assigns each company a long-term “issuer” rating to measure the company’s ability to meet senior obligations and also issues specific ratings for each debt issuance according to the debt contract. S&P uses the Watchlist for issuers, a specific issue, or for preferred stock. I am focusing

---

33 I cannot rule out the possibility that firms cut advertising expenses, R&D, and/or SG&A expenses due to financial constraints rather than to managers’ intentions to manage earnings.
on the long term issuer Watchlist in this study in order to investigate the relation between CRAs and firm-level information.\(^{34}\)

There are three types of long term issuer Watchlists: negative (NEG), positive (POS), and developing (DEV), indicating possible downgrade, upgrade, and uncertain outcome, respectively. The decisions to place an issuer on the Watchlist and to remove an issuer from the Watchlist are made by separate rating committees. When an issuer is on the Watchlist, S&P may contact the issuer’s management to gather information regarding the issuer’s situation and any potential plans it may have to address the possible credit risk change.

S&P generated 13,333 Watchlist actions (8,954 on NEG, 3,089 on POS, and 1,290 on DEV) in the 27-year period beginning in 1981 (the inception of the Watchlist) and ending in 2007.\(^{35}\) For multiple NEG watch placements, I keep the first NEG watch observation in my sample.\(^{36}\) I then match NEG Watchlist issuers with other issuers who did not have any Watchlist placements during the two years surrounding the NEG Watchlist announcement. I match the first two digits of the industry classification code (the US SIC classification). The final NEG watch sample includes 438 firms, and the control sample includes 13,565 observations. The requirement of having returns available to measure the news limits my sample size.

Panel A of Table I presents summary statistics of CARs for the NEG Watchlist sample by rating category. The mean (median) CARs are -0.078 (-0.045), -0.059 (-0.035), and -0.085 (-0.094) for High Grade, Medium Grade, and Low Grade respectively. Panel B of Table I presents summary statistics of CARs for the control sample by rating category. The mean (median) CARs are -0.012 (-0.015), -0.004 (-0.009), and -0.017 (-0.027) for High Grade, Medium Grade, and Low Grade.

\(^{34}\) Issuer ratings and issuer rating changes are usually consistent with senior issue ratings and rating changes (Ashbaugh-Skaife et al. 2006).

\(^{35}\) I exclude Watchlist actions for unsolicited ratings (e.g. pi ratings), that is, the ratings issued by S&P using only public information of the issuers. Issuers do not pay for unsolicited ratings.

\(^{36}\) S&P placed a firm on the NEG Watchlist in my initial NEG Watchlist sample five times on average during the 27-year period.
respectively. Overall, the NEG Watchlist sample (mean: -0.064; median: -0.043) faces more negative news than the control sample does (mean: -0.007; median: -0.011).

Table II presents the industry distribution of both the NEG Watchlist sample and the control sample. While the percentages of firms on the NEG Watchlist in Durable Manufacturers and Financial Institutions, Insurance and Real Estate are about four percent lower than are those in the control sample in the same industries, the percentages of firms on the NEG Watchlist in Automotive, Services, Textiles and Printing/Publishing industries are two or three percent higher than are those in the control sample in the same industries. Overall, the distribution of firms across industries is similar for NEG Watchlist firms and control firms.  

B. The Watchlist Sample for Testing Earnings Management

My sample spans the years 1988 - 2007. The sample size for testing earnings management activities on the NEG Watchlist is 520 (765) firm-year observations for the group with rating confirmations (downgrades). The sample size on the POS Watchlist is 107 (335) firm-year observations for the group with rating confirmations (upgrades). The samples are small because of the data required to compute earnings management measures.

V. Results

A. The Credit Watch as a Mechanism for Monitoring and Implicit Contracting

Table III presents the results of estimating the logit model (1). The coefficient estimate on $NEWS^{*}ICQ$, 0.522, is significant with the expected sign and a two-tailed p-value of 0.080. While

37 Unreported $\chi^2$ test statistics indicate that the percentage differences between the NEG watchlist sample and the control sample are significant at least at the ten percent level. I cannot estimate the $\chi^2$ statistic for the automotive industry because the percentage of the firms in the automotive industry is less than 5% in both the test and control samples, thus violating the assumptions needed to reliably measure the $\chi^2$ statistic.

38 My sample period begins in 1988 because cash flow statements are not available until 1988 (SFAS No. 95 took effect in fiscal 1988).

39 The pseudo $R^2$ (0.002) is low because the number of observations placed on the NEG Watchlist is much lower than the number of observations not placed on any Watchlist. Furthermore, I constructed a control sample by matching...
the coefficient estimate on NEWS, 0.575, is significant, the coefficient estimate on ICQ, 0.089, is not. 40,41 These results are consistent with H1a and thus support BMS’s proposition #5 that intermediate credit quality firms are more likely to appear on the Watchlist in response to negative news. These results are also consistent with CRAs allocating more time and/or resources where the expected benefits are highest. Overall, the results support BMS’s "focal point" theory about the credit watch procedure, in particular, the signaling effect of the credit watch, together with the implicit contract and monitoring relationship between CRAs and firms on the Watchlist.

**B. Earnings Management and the Credit Watch Process**

Table IV presents the results of earnings management through manipulation of accruals and real operating activities while on the Watchlist (year \( t \)) and during the fiscal year immediately preceding the year on the Watchlist (year \( t-1 \)). Columns (2) – (4) present results for the two groups of firms on the NEG Watchlist, while columns (5) – (7) present the results for the two groups of firms on the POS Watchlist.

Overall, it appears that firms generally manage earnings upward in both the year before and the year during Watchlist observation. For example, in both the negative Watchlist confirmation and downgrade samples, the estimates of discretionary accruals and abnormal cash from operations are significantly positive in both years \( t \) and \( t-1 \). However, I do not find significantly more earnings management in year \( t \) relative to year \( t-1 \), and I do not find significant differences in earnings management for the downgrade and confirmation samples.

<table>
<thead>
<tr>
<th>Column</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2) – (4)</td>
<td>Results for the two groups of firms on the NEG Watchlist</td>
</tr>
<tr>
<td>(5) – (7)</td>
<td>Results for the two groups of firms on the POS Watchlist</td>
</tr>
</tbody>
</table>

Industry and size and running the logit regressions. Nonetheless, the control sample approach may be subject to oversampling problems because the number of Watchlist observations is very small relative to the number of all issuers. The low pseudo \( R^2 \) could be also due to an omitted correlated variable problem.

Before I run the logit model (1), I employ two indicators in my estimation: LCQ (where LCQ =1 if the rating is below BB-; = 0, otherwise) and HCQ (where HCQ =1 if rating is between AAA and AA-; = 0, otherwise) and the two interaction terms (NEWS*LCQ and NEWS*HCQ) are included as well. In other words, I use ICQ firms as a reference group. The results suggest that both HCQ and LCQ firms are less likely to be placed on the NEG Watchlist than are ICQ firms in response to bad news.

When the model includes NEWS and ICQ but not the interaction term, the pseudo \( R^2 \) is slightly reduced from 0.0021 to 0.0019. The coefficient estimate on NEWS is significant, and the coefficient estimate on ICQ is not.
I can reject the hypothesis of equivalent earnings management in the confirmation and upgrade/downgrade samples in only one case. It appears that positive Watchlist firms coming off the Watchlist with confirmations manage discretionary expenses downward to a significantly greater degree in year \( t \) than in year \( t-1 \). Further, this difference is significantly greater than the (statistically insignificant) difference in manipulation of discretionary expenses between years \( t \) and \( t-1 \) for the upgrade sample on the positive Watchlist. Similarly, in year \( t \) relative to year \( t-1 \), I find significantly more downward manipulation of discretionary expenses in the downgrade sample of firms on the negative Watchlist; whereas, the confirmation sample exhibits (insignificantly) less downward manipulation of discretionary expenses in year \( t \) relative to year \( t-1 \).

Thus, it appears that credit analysts see through attempts of firms to manage perceptions through the manipulation of discretionary expenses, and perhaps this behavior is associated with CRAs’ perceptions of other characteristics that make positive (negative) Watchlist firms poor candidates for credit upgrades (confirmations). As explained in Section II.B, CRAs may take into account other factors including the firms’ reputation and/or quality of management, cost structure, type of assets, and financial structure when assessing the likelihood of successful restorations of credit quality for firms on the Watchlist.\(^{42}\) CRAs may perceive the reputation and/or quality of management in firms with earnings management as low and thus assess these firms as less able to restore their credit quality. For example, Seybert’s (2009) experiment suggests that reputation concerns contribute to real earnings management in the form of overinvestment in continuing projects in the context of R&D capitalization. Overall, the results in Table IV provide some evidence of earnings management through manipulation of accruals and real activities but I find no evidence that the CRA is fooled by this behavior.\(^{43}\) In fact, I have some evidence to suggest that the

\(^{42}\) Lucas (1978) proposes a model where the quality of firm managers affects the firms’ operating decisions. Given the same quantity of labor and capital, he predicts that firms with higher quality management will produce more output.

\(^{43}\) Results are robust when using performance matched discretionary accruals.
CRA perceives the quality of management as low, in positive (negative) Watchlist firms that manage real activities to influence CRA perceptions, and thus the CRA does not upgrade (confirm) these firms’ credit ratings.

VI. Conclusions and Future Research

CRAs have suffered significant negative media attention in relation to the recent economic crisis. For example,

The ratings agencies are perhaps the biggest contributors to the crisis. They happily rated ultra-risky subprime securities AAA. It is named subprime for a reason. No amount of financial engineering can change that fact, and the rating agencies should have known it. Fee income drove decisions, instead of common sense. The latest blunder is that of reaffirming the ratings of the bond insurers (Dow Jones & Company May 5, 2008 Wall Street Journal).

When regulators and investors criticized CRAs for their role in the credit crisis, John C. Dugan, Comptroller of the Currency, spoke in support of CRAs in a speech to the Enterprise Annual Network Conference:

CRA is not the culprit behind the subprime mortgage lending abuses, or the broader credit quality issues in the marketplace. Indeed, the lenders most prominently associated with subprime mortgage lending abuses and high rates of foreclosure are lenders not subject to CRA. … During the community tours I have taken over the past three years, I personally witnessed the positive impact that CRA partnerships have had in transforming communities, expanding homeownership, and promoting job creation and economic development.

Ongoing and intense debate surrounding the question of CRA responsibility for the credit crisis has inspired my research inquiry and shaped my choice of research questions. I investigate two important research questions in the context of the credit watch process. First, I examine the monitoring role of CRAs through the credit watch process. Second, I examine whether CRAs take rating actions reflecting adjustments for earnings management surrounding the credit watch event.
This study has two important findings. First, results from a logit model are consistent with the BMS proposition that the CRA monitoring role is most beneficial in the wake of bad news for firms of intermediate grade credit quality. In addition, I document that firms on the positive Watchlist with later rating confirmations are more likely to manage earnings upward, through manipulation of discretionary expenses, than are firms on the same Watchlist with later upgrades. This pattern suggests that credit analysts take rating actions that reflect adjustments for earnings management, and firms’ earnings management behavior is perhaps associated with other quality characteristics that make the firms poor candidates for favorable CRA ratings decisions.

Although public accounting information is important for CRAs' decisions in assessing credit risk (Blume et al. 1998; Ederington et al. 1987; Iskandar-Datta et al. 1994; Jorion et al. 2009; Kaplan and Urwitz 1979; Ziebart and Reiter 1992), prior literature provides little empirical evidence regarding whether CRAs efficiently impound accounting information when assessing credit risk and whether the credit watch process is associated with greater CRA efficiency. To address these questions in future research, I will employ a prediction model of the likelihood of default (Chava and Jarrow 2004; Shumway 2001). The model will employ a dynamic approach following Campbell et al. (2008), which estimates the probabilities of defaults over the next period conditional on the survival of issuers.

Also, in further research, I plan to employ alternative measures for economic news to test BMS’s propositions. One alternative measure is based on accounting variables. CRAs emphasize cash flow analysis in their rating process. S&P (2008a p. 7) states, “Cash flow analysis is usually the single most critical aspect of credit rating decisions. It takes on added importance for speculative-grade issuers.”

In addition, S&P specifies the factors they consider when performing cash flow analysis:
Cash flow analysis focuses on understanding and forecasting how cash is generated and spent by a business. It incorporates identifying a company's cash flows, determining trends and sustainability, distinguishing operating from investing and financing flows, and understanding potential sources of distortion and future volatility. An enterprise's capacity to pay debts or any other obligation, the core underlying concept of a credit rating, is determined by the ability to generate cash—not earnings, which is an accounting concept. Although there is generally a strong correlation between operating cash flow and profitability in the long run, many transactions and accounting entries may affect one and not the other during a specific period. (S&P 2008a p. 39)

Thus, I plan to compute a news score based on accounting variables giving more weight to cash flow. Another alternative measure for economic news is the surprise factor between the released value of scheduled economic announcements and the consensus forecasts from Money Market Services (MMS) (Balduzzi et al. 2001; McQueen and Roley 1993; Urich and Wachtel 1984).\(^{44}\)

Finally, I plan to test two other predictions that emerge from the BMS theory of the economic benefits associated with the credit watch process. One prediction predicts positive (negative) market reaction to rating confirmations (downgrades) after the conclusion of the negative credit watch and also predicts that, if the CRA downgrades the firm’s debt after the conclusion of the credit watch, the negative market reaction is negatively associated with the magnitude of the initial stock price response to the bad news. The S&P credit rating database does not clearly provide the credit watch resolution date. In future research, I plan to use issue watch data from Mergent FISD to test this prediction. Another BMS prediction suggests that the market reaction to credit watch announcements is conditional on the market expectation for the likelihood of successful restorations of the firms’ credit quality. I plan to develop appropriate proxies for market expectations of successful credit quality restoration.

Overall, this study provides insight regarding the economic benefits of the credit watch process and the monitoring role of credit analysts, and evidence of firms’ attempts to manage credit analyst

\(^{44}\) MMS has conducted telephone surveys since late 1977. The MMS data are very frequently used in research of economic announcements of unemployment, CPI, and industrial production, among others.
perceptions in the context of their decisions during the credit watch process. Further, this study informs us about whether credit analysts’ decisions efficiently account for the effects of earnings management on their perceptions of firms’ credit quality. In future work, I will continue to explore the role of credit analysts in the interpretation of accounting information for the efficient operation of U.S. and global debt markets.
## Appendix

### Average Cumulative Credit Loss Rates by Letter Rating, 1982-2008

<table>
<thead>
<tr>
<th>Rating</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Year 4</th>
<th>Year 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aaa</td>
<td>0.00%</td>
<td>0.02%</td>
<td>n.a.</td>
<td>0.00%</td>
<td>0.02%</td>
</tr>
<tr>
<td>Aa</td>
<td>0.01%</td>
<td>0.04%</td>
<td>0.05%</td>
<td>0.07%</td>
<td>0.14%</td>
</tr>
<tr>
<td>A</td>
<td>0.02%</td>
<td>0.07%</td>
<td>0.17%</td>
<td>0.30%</td>
<td>0.40%</td>
</tr>
<tr>
<td>Baa</td>
<td>0.11%</td>
<td>0.28%</td>
<td>0.52%</td>
<td>0.78%</td>
<td>1.10%</td>
</tr>
<tr>
<td>Ba</td>
<td>0.60%</td>
<td>1.83%</td>
<td>3.33%</td>
<td>4.93%</td>
<td>6.27%</td>
</tr>
<tr>
<td>B</td>
<td>2.73%</td>
<td>6.35%</td>
<td>9.79%</td>
<td>12.69%</td>
<td>14.53%</td>
</tr>
<tr>
<td>Caa-C</td>
<td>10.50%</td>
<td>17.25%</td>
<td>22.78%</td>
<td>24.51%</td>
<td>26.70%</td>
</tr>
<tr>
<td>Investment Grade</td>
<td>0.04%</td>
<td>0.13%</td>
<td>0.24%</td>
<td>0.37%</td>
<td>0.52%</td>
</tr>
<tr>
<td>Speculative Grade</td>
<td>2.77%</td>
<td>5.72%</td>
<td>8.50%</td>
<td>10.69%</td>
<td>12.24%</td>
</tr>
<tr>
<td>All Rated</td>
<td>0.99%</td>
<td>2.01%</td>
<td>2.93%</td>
<td>3.64%</td>
<td>4.15%</td>
</tr>
</tbody>
</table>
References


### Figure 1
Sequence of Events

<table>
<thead>
<tr>
<th>Time</th>
<th>Event Description</th>
</tr>
</thead>
</table>
| $t = 0$ | *Firm $i$ announces to use debt financing to invest in a new project*
| $t = 1$ | *A CRA initiates a credit watch procedure*<br> *Firm $i$ chooses whether to undertake recovery effort* |
| $t = 2$ | *After observing the recovery effort and its success or failure, the CRA assigns a new rating or confirms the old rating* |
| $t = 3$ | *The project’s payoff is realized*<br> *Firm $i$ either repays its debt or defaults* |

On the watch:
- S&P: 89 days (NEG); 111 days (POS); and 116 days (DEV)
- Moody’s: 85 days (NEG); 93 days (POS); and 92 days (DEV).

*CRAs prefer to remove firms from the Watchlist within 90 days. Median values are reported.*
### Table I

**Summary Statistics**

Panel A  NEG Watch Firms

<table>
<thead>
<tr>
<th>S&amp;P Initial Long Term Issuer Ratings&lt;sup&gt;a&lt;/sup&gt;</th>
<th>No. obs.</th>
<th>Q1</th>
<th>Mean</th>
<th>Median</th>
<th>Q3</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>3</td>
<td>-0.372</td>
<td>-0.213</td>
<td>-0.284</td>
<td>0.017</td>
<td>0.204</td>
</tr>
<tr>
<td>AA+</td>
<td>5</td>
<td>-0.204</td>
<td>-0.096</td>
<td>-0.060</td>
<td>-0.001</td>
<td>0.108</td>
</tr>
<tr>
<td>AA</td>
<td>12</td>
<td>-0.104</td>
<td>-0.061</td>
<td>-0.061</td>
<td>0.042</td>
<td>0.158</td>
</tr>
<tr>
<td>AA-</td>
<td>11</td>
<td>-0.081</td>
<td>-0.051</td>
<td>-0.067</td>
<td>0.004</td>
<td>0.065</td>
</tr>
<tr>
<td>High Grade</td>
<td>31</td>
<td>-0.149</td>
<td>-0.078</td>
<td>-0.045</td>
<td>0.017</td>
<td>0.131</td>
</tr>
<tr>
<td>A+</td>
<td>18</td>
<td>-0.071</td>
<td>0.011</td>
<td>0.029</td>
<td>0.110</td>
<td>0.142</td>
</tr>
<tr>
<td>A</td>
<td>36</td>
<td>-0.125</td>
<td>-0.036</td>
<td>-0.024</td>
<td>0.064</td>
<td>0.175</td>
</tr>
<tr>
<td>A-</td>
<td>31</td>
<td>-0.186</td>
<td>-0.068</td>
<td>-0.086</td>
<td>0.045</td>
<td>0.142</td>
</tr>
<tr>
<td>BBB+</td>
<td>35</td>
<td>-0.177</td>
<td>-0.019</td>
<td>-0.009</td>
<td>0.116</td>
<td>0.221</td>
</tr>
<tr>
<td>BBB</td>
<td>63</td>
<td>-0.107</td>
<td>0.015</td>
<td>0.012</td>
<td>0.125</td>
<td>0.192</td>
</tr>
<tr>
<td>BBB-</td>
<td>36</td>
<td>-0.313</td>
<td>-0.098</td>
<td>-0.054</td>
<td>0.175</td>
<td>0.324</td>
</tr>
<tr>
<td>BB+</td>
<td>22</td>
<td>-0.291</td>
<td>-0.139</td>
<td>-0.192</td>
<td>0.028</td>
<td>0.212</td>
</tr>
<tr>
<td>BB</td>
<td>48</td>
<td>-0.259</td>
<td>-0.085</td>
<td>-0.108</td>
<td>0.108</td>
<td>0.347</td>
</tr>
<tr>
<td>BB-</td>
<td>42</td>
<td>-0.380</td>
<td>-0.141</td>
<td>-0.129</td>
<td>0.107</td>
<td>0.432</td>
</tr>
<tr>
<td>Medium Grade</td>
<td>331</td>
<td>-0.208</td>
<td>-0.059</td>
<td>-0.035</td>
<td>0.101</td>
<td>0.275</td>
</tr>
<tr>
<td>B+</td>
<td>40</td>
<td>-0.193</td>
<td>-0.039</td>
<td>-0.084</td>
<td>0.061</td>
<td>0.293</td>
</tr>
<tr>
<td>B</td>
<td>23</td>
<td>-0.488</td>
<td>-0.033</td>
<td>-0.050</td>
<td>0.141</td>
<td>0.513</td>
</tr>
<tr>
<td>B-</td>
<td>6</td>
<td>-0.437</td>
<td>-0.195</td>
<td>-0.282</td>
<td>-0.012</td>
<td>0.323</td>
</tr>
<tr>
<td>CCC, CC, and C</td>
<td>7</td>
<td>-0.874</td>
<td>-0.422</td>
<td>-0.283</td>
<td>-0.134</td>
<td>0.377</td>
</tr>
<tr>
<td>Low Grade</td>
<td>76</td>
<td>-0.293</td>
<td>-0.085</td>
<td>-0.094</td>
<td>0.061</td>
<td>0.392</td>
</tr>
<tr>
<td>Total</td>
<td>438</td>
<td>-0.211</td>
<td>-0.064</td>
<td>-0.043</td>
<td>0.072</td>
<td>0.291</td>
</tr>
<tr>
<td>S&amp;P Initial Long Term Issuer Ratings&lt;sup&gt;a&lt;/sup&gt;</td>
<td>No. obs.</td>
<td>Q1</td>
<td>Mean</td>
<td>Median</td>
<td>Q3</td>
<td>Std Dev</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
<td>----------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>AAA</td>
<td>203</td>
<td>-0.122</td>
<td>-0.031</td>
<td>-0.035</td>
<td>0.053</td>
<td>0.146</td>
</tr>
<tr>
<td>AA+</td>
<td>113</td>
<td>-0.108</td>
<td>-0.003</td>
<td>-0.016</td>
<td>0.060</td>
<td>0.150</td>
</tr>
<tr>
<td>AA</td>
<td>418</td>
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<td>-0.011</td>
<td>-0.011</td>
<td>0.070</td>
<td>0.132</td>
</tr>
<tr>
<td>AA-</td>
<td>502</td>
<td>-0.088</td>
<td>-0.007</td>
<td>-0.010</td>
<td>0.066</td>
<td>0.140</td>
</tr>
<tr>
<td>High Grade</td>
<td>1,236</td>
<td>-0.096</td>
<td>-0.012</td>
<td>-0.015</td>
<td>0.066</td>
<td>0.139</td>
</tr>
<tr>
<td>A+</td>
<td>799</td>
<td>-0.087</td>
<td>0.001</td>
<td>-0.002</td>
<td>0.084</td>
<td>0.159</td>
</tr>
<tr>
<td>A</td>
<td>1,312</td>
<td>-0.100</td>
<td>-0.100</td>
<td>-0.007</td>
<td>0.086</td>
<td>0.160</td>
</tr>
<tr>
<td>A-</td>
<td>1,100</td>
<td>-0.096</td>
<td>-0.004</td>
<td>-0.011</td>
<td>0.079</td>
<td>0.167</td>
</tr>
<tr>
<td>BBB+</td>
<td>1,240</td>
<td>-0.109</td>
<td>-0.008</td>
<td>-0.010</td>
<td>0.099</td>
<td>0.194</td>
</tr>
<tr>
<td>BBB</td>
<td>1,426</td>
<td>-0.119</td>
<td>-0.119</td>
<td>-0.012</td>
<td>0.101</td>
<td>0.193</td>
</tr>
<tr>
<td>BBB-</td>
<td>1,122</td>
<td>-0.118</td>
<td>0.002</td>
<td>-0.003</td>
<td>0.125</td>
<td>0.234</td>
</tr>
<tr>
<td>BB+</td>
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<td>-0.159</td>
<td>-0.013</td>
<td>-0.017</td>
<td>0.128</td>
<td>0.270</td>
</tr>
<tr>
<td>BB</td>
<td>1,013</td>
<td>-0.167</td>
<td>0.002</td>
<td>0.003</td>
<td>0.158</td>
<td>0.297</td>
</tr>
<tr>
<td>BB-</td>
<td>1,245</td>
<td>-0.195</td>
<td>-0.008</td>
<td>-0.019</td>
<td>0.190</td>
<td>0.349</td>
</tr>
<tr>
<td>Medium Grade</td>
<td>9,995</td>
<td>-0.121</td>
<td>-0.004</td>
<td>-0.009</td>
<td>0.109</td>
<td>0.232</td>
</tr>
<tr>
<td>B+</td>
<td>1,267</td>
<td>-0.218</td>
<td>-0.015</td>
<td>-0.027</td>
<td>0.196</td>
<td>0.370</td>
</tr>
<tr>
<td>B</td>
<td>546</td>
<td>-0.293</td>
<td>-0.013</td>
<td>-0.011</td>
<td>0.234</td>
<td>0.517</td>
</tr>
<tr>
<td>B-</td>
<td>289</td>
<td>-0.324</td>
<td>-0.062</td>
<td>-0.062</td>
<td>0.194</td>
<td>0.505</td>
</tr>
<tr>
<td>CCC, CC, and C</td>
<td>232</td>
<td>-0.310</td>
<td>0.013</td>
<td>0.014</td>
<td>0.341</td>
<td>0.773</td>
</tr>
<tr>
<td>Low Grade</td>
<td>2,334</td>
<td>-0.252</td>
<td>-0.017</td>
<td>-0.027</td>
<td>0.215</td>
<td>0.477</td>
</tr>
<tr>
<td>Total</td>
<td>13,565</td>
<td>-0.133</td>
<td>-0.007</td>
<td>-0.011</td>
<td>0.115</td>
<td>0.284</td>
</tr>
</tbody>
</table>

<sup>a</sup> Issuer credit ratings: an opinion of the obligor's overall capacity and willingness to meet its financial obligations as they come due. A long-term issuer rating measures a company’s ability to meet its senior obligations. Watchlist actions for unsolicited ratings (e.g. pi ratings are excluded. Sample period is from 1981 to 2007.


There are three types of long term issuer Credit Watch designations: positive (POS), negative (NEG), and developing (DEV). POS means that the rating may be raised. NEG means that the ratings may be lowered. DEV is used for those unusual situations in which future events are so unclear that the rating could be raised or lowered. Cumulative abnormal returns (CAR) represents market and risk-adjusted returns over the 90 days prior to placement on the Watchlist or since the day prior to the most recent quarterly earnings announcement, whichever period is longer. CARs are computed as the firm’s raw return minus the expected return based on the market model estimated over the 250 days prior to the abnormal return accumulation period.
### Table II
Industry Distribution

<table>
<thead>
<tr>
<th>Industry</th>
<th>No. of Firms on NEG</th>
<th>Percentage of Firms on NEG</th>
<th>No. of Control Firms (not on Watch)</th>
<th>Percentage of Control Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>2</td>
<td>0.46</td>
<td>17</td>
<td>0.13</td>
</tr>
<tr>
<td>Automotive</td>
<td>15</td>
<td>3.42</td>
<td>144</td>
<td>1.06</td>
</tr>
<tr>
<td>Chemicals</td>
<td>19</td>
<td>4.34</td>
<td>465</td>
<td>3.43</td>
</tr>
<tr>
<td>Computers</td>
<td>24</td>
<td>5.48</td>
<td>842</td>
<td>6.21</td>
</tr>
<tr>
<td>Durable Manufacturers</td>
<td>57</td>
<td>13.01</td>
<td>2,326</td>
<td>17.15</td>
</tr>
<tr>
<td>Extractive</td>
<td>31</td>
<td>7.08</td>
<td>1,099</td>
<td>8.10</td>
</tr>
<tr>
<td>Financial Institutions, Insurance and Real Estate</td>
<td>52</td>
<td>11.87</td>
<td>2,126</td>
<td>15.67</td>
</tr>
<tr>
<td>Food</td>
<td>12</td>
<td>2.74</td>
<td>346</td>
<td>2.55</td>
</tr>
<tr>
<td>Mining and Construction</td>
<td>13</td>
<td>2.97</td>
<td>301</td>
<td>2.22</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>2</td>
<td>0.46</td>
<td>65</td>
<td>0.48</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>11</td>
<td>2.51</td>
<td>275</td>
<td>2.03</td>
</tr>
<tr>
<td>Retail</td>
<td>47</td>
<td>10.73</td>
<td>1,474</td>
<td>10.87</td>
</tr>
<tr>
<td>Services</td>
<td>38</td>
<td>8.68</td>
<td>864</td>
<td>6.40</td>
</tr>
<tr>
<td>Textiles and Printing/Publishing</td>
<td>37</td>
<td>8.45</td>
<td>724</td>
<td>5.34</td>
</tr>
<tr>
<td>Transportation</td>
<td>38</td>
<td>8.68</td>
<td>1,201</td>
<td>8.85</td>
</tr>
<tr>
<td>Utilities</td>
<td>40</td>
<td>9.13</td>
<td>1,296</td>
<td>9.55</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>438</strong></td>
<td><strong>100%</strong></td>
<td><strong>13,565</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

Industry classifications are compiled using the following U.S. SIC codes: agriculture (0100-0999), mining and construction (1000-1999, excluding 1300-1399), food (2000-2111), textiles and printing/publishing (2200-2780), chemicals (2800-2824, 2840-2899), pharmaceuticals (2830-2836); extractive (2900-2999, 1300-1399); durable manufacturers (3000-3999 excluding 3570-3579 and 3670-3679), automotive industry (3711 and 3714), computers (7370-7379, 3570-3579, 3670-3679), transportation (4000-4899), utilities (4000-4999), retail (5000-5999), financial institutions, insurance and real estate companies (6000-6999), services (7000-8999 excluding 7370-7379) and Miscellaneous (9000-9999). Sample period is from 1981 to 2007.
## Table III

**Association between Placement on the NEG Watchlist, News, and Credit Rating**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Predicted</th>
<th>Clustered</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Sign</td>
</tr>
<tr>
<td>NEWS</td>
<td>?</td>
<td>0.575***</td>
</tr>
<tr>
<td>ICQ</td>
<td>?</td>
<td>0.089</td>
</tr>
<tr>
<td>NEWS*ICQ</td>
<td>+</td>
<td>0.522*</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>-3.525***</td>
</tr>
</tbody>
</table>

NEG Watch obs. 438  
Control obs. 13,565  
pseudo- R² 0.002

Logit model:

\[
P(Y_{ij} = 1) = \frac{1}{1 + \exp (-\alpha - \beta x_{ij})}
\]

where \( Y_{ij} \) is an indicator that equals one if the firm is placed on the NEG Watchlist in month \( j \) and otherwise zero, and \( x_{ij} \) is a vector of explanatory variables. Sample period is from 1981 to 2007. \( NEWS \) is cumulative abnormal returns (CARs) multiplied by negative one, where CARs represents market and risk-adjusted returns over the 90 days prior to placement on the Watchlist or since the day prior to the most recent quarterly earnings announcement, whichever period is longer. CARs are computed as the firm’s raw return minus the expected return based on the market model estimated over the 250 days prior to the abnormal return accumulation period. \( ICQ_{it} = 1 \) if a firm’s rating prior to the Watchlist is between A+ and BB- ; = 0, otherwise.
### Table IV
Results of Accrual-Based Earnings Management and Real Earnings Management Activities

<table>
<thead>
<tr>
<th>Measures</th>
<th>NEG</th>
<th>POS</th>
<th>DIFG&lt;sup&gt;a&lt;/sup&gt; (C - D)</th>
<th>NEG</th>
<th>POS</th>
<th>DIFG&lt;sup&gt;a&lt;/sup&gt; (C - U)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Confirmation</td>
<td>Downgrade</td>
<td></td>
<td>Confirmation</td>
<td>Upgrade</td>
<td></td>
</tr>
<tr>
<td>$DA_{t-1}$</td>
<td>0.282***</td>
<td>0.165***</td>
<td>0.117</td>
<td>0.015</td>
<td>0.196*</td>
<td>-0.181</td>
</tr>
<tr>
<td>$DA_t$</td>
<td>0.325***</td>
<td>0.286***</td>
<td>0.039</td>
<td>-0.011</td>
<td>0.375***</td>
<td>-0.386</td>
</tr>
<tr>
<td>$DADIFY&lt;sup&gt;b&lt;/sup&gt;$</td>
<td>0.043</td>
<td>0.121</td>
<td>-0.077</td>
<td>-0.026</td>
<td>0.178</td>
<td>-0.205</td>
</tr>
<tr>
<td>Abnormal CFO$_{t-1}$</td>
<td>0.237***</td>
<td>0.221***</td>
<td>0.016</td>
<td>0.127***</td>
<td>0.306***</td>
<td>-0.179</td>
</tr>
<tr>
<td>Abnormal CFO$_t$</td>
<td>0.245***</td>
<td>0.266***</td>
<td>-0.021</td>
<td>0.244*</td>
<td>0.216***</td>
<td>0.028</td>
</tr>
<tr>
<td>CFODIFY&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.007</td>
<td>0.044</td>
<td>-0.037</td>
<td>0.116</td>
<td>-0.090</td>
<td>0.206</td>
</tr>
<tr>
<td>Abnormal Prod$_{t-1}$</td>
<td>-0.001</td>
<td>0.019*</td>
<td>-0.021</td>
<td>-0.011</td>
<td>-0.014</td>
<td>0.002</td>
</tr>
<tr>
<td>Abnormal Prod$_t$</td>
<td>0.022</td>
<td>0.024*</td>
<td>-0.002</td>
<td>-0.018</td>
<td>-0.052**</td>
<td>0.033</td>
</tr>
<tr>
<td>ProdDIFY&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.023</td>
<td>0.004</td>
<td>0.018</td>
<td>-0.008</td>
<td>-0.038*</td>
<td>0.030</td>
</tr>
<tr>
<td>Abnormal DiscExp$_{t-1}$</td>
<td>-1.193***</td>
<td>-0.735*</td>
<td>-0.458</td>
<td>0.187</td>
<td>-1.197***</td>
<td>1.384*</td>
</tr>
<tr>
<td>Abnormal DiscExp$_t$</td>
<td>-0.763</td>
<td>-1.614***</td>
<td>0.851</td>
<td>-1.229***</td>
<td>-0.814***</td>
<td>-0.416</td>
</tr>
<tr>
<td>DiscExpDIFY&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.430</td>
<td>-0.879*</td>
<td>1.309</td>
<td>-1.417*</td>
<td>0.383</td>
<td>-1.800*</td>
</tr>
<tr>
<td>Obs #</td>
<td>520</td>
<td>765</td>
<td>1,285</td>
<td>107</td>
<td>335</td>
<td>442</td>
</tr>
</tbody>
</table>

Sample period is from 1988 to 2007. Mean is reported for each measure in each group. Median is not reported because of no significant results.

*** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Two tailed test.

<sup>a</sup> DIFG denotes the difference in earnings management measures between two groups.

<sup>b</sup> DIFY denotes the difference in earnings management measures for each group (a later downgrade, a later upgrade, and a rating confirmation) between the year being on the Watchlist (year $t$) and the year immediately preceding the year being on the Watchlist (year $t-1$).

Abnormal CFO$_t$: abnormal cash flows from operations; Abnormal DiscExp$_t$: abnormal discretionary expenditures (following Roychowdhury’s (2006) and Gunny’s (2009) models); Abnormal Prod$_t$: abnormal production costs (following Roychowdhury’s (2006) and Gunny’s (2009) models); $DA_{t-1}$: discretionary accruals measure by the modified Jones model or performance-matched discretionary accruals (Kothari et al. 2005); discretionary accruals by the modified Jones model are reported.