Characteristics and Information Value of Credit Watches

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We analyze credit watch and rating actions to better understand the role of credit watches in the credit rating process. We find that watch actions are more frequently prompted by specific, publicly known events than are rating actions. The likelihood that a watch action precedes a rating action varies systematically with proxies for investor demand for credit quality information and the adverse consequences of issuing a rating change prematurely. Credit watches occur more often in response to deterioration in credit quality, and issuers make concerted efforts to address the concerns that prompted down watches. Down watches are less likely than up watches to indicate the direction of the subsequent rating change. Watch announcements are associated with abnormal stock returns, indicating that credit watch actions are significant information events. Our results suggest that credit watches are informative and facilitate the stability of ratings by allowing firms to correct deficiencies and prevent downgrades.

Credit rating agencies (CRAs) issue credit watches to indicate the potential direction of a rating change that might follow the resolution of specific events or trends. Credit watches play an increasingly important role in the credit rating process. For example, the ratio of Moody's watch actions to all ratings actions increased from 28% during the 1992 to 1996 period to 47% during the 2002 to 2010 period.[1] Furthermore, Credit watches increase default prediction accuracy and convey information to market participants.[2] However, despite their importance, the role of credit watches has received little study. In this paper, we provide empirical evidence concerning the role of credit watches in the credit rating process using a sample of 4,539 credit watches and 10,790 rating actions issued by Moody's from 1992 through 2010.

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[1] As a further example of the prevalence of watch actions, 17% of a recent sample of Standard & Poor's (S&P's) rating action press releases referred to watch actions.

[2] Using a data set covering 1996–2003, Cantor and Mann (2006) find that issuers with up watches (down watches) and stable outlooks exhibit default rates similar to those of issuers with credit ratings two notches higher (lower). Also see Fons, Cantor, and Mahoney (2002), Hamilton and Cantor (2005, 2004), and Dionne, Gauthier, Hammami, Maurice, and Simonato (2010).

Our analysis of credit watches is motivated by their importance in the credit rating process, and many issues on the value of credit ratings resulting from apparent failures in the credit rating process.[3] Congress and regulators have paid close attention to the alleged inadequacy of CRAs' disclosures about their rating procedures, analytical methods, and criteria.[4] The Credit Rating Agency Reform Act of 2006 requires CRAs to describe their procedures and methodologies for determining credit ratings.[5] However, CRAs provide minimal information about their credit watch procedures, even though they consider watch actions to be formal rating actions.[6] Such information is particularly important due to the close link between credit watch actions and CRAs' stated practice of monitoring credit ratings after they are issued.[7]

We investigate whether credit watches are used in a manner consistent with the dual role of CRAs as both providers of information and suppliers of ratings that are sufficiently stable and reliable to be used in contracting.[8] We hypothesize that CRAs are more likely to issue credit watches when demand for information is greater and that credit watches are more likely than rating changes to be triggered by discrete events, since such events might signal a potential (but potentially avoidable) change in credit quality. We also test various implications of a model proposed by Boot, Milbourn, and Schmeits (2006). For instance, Boot et al. (2006) predict that the credit watch procedure will be invoked more often in response to a deterioration than to an improvement in credit quality and that it is less likely for a down watch to be followed by a rating down grade than for an up watch likely to be followed by a rating upgrade. In addition, Boot et al. (2006) put forward a number of conjectures regarding the market responses to the issuance and resolution of credit watches. For example, Boot et al. (2006) predict that those rating changes that are preceded by a credit watch are more informative than those rating changes that are not preceded by a watch action, and that the market impact of a rating downgrade is larger if the market impact of the preceding credit watch is smaller.

We show that credit watch actions and rating actions have different triggering events and underlying causes. A high percentage (59.1%) of credit watch actions are prompted by specific, publicly known events (e.g., mergers or acquisitions), whereas only 21.4% of rating changes are triggered by such events. Also, acquisitions, targets, mergers, and restructuring events are much

[3] The massive accounting scandals of 2000–2002, in particular the highly publicized failure of Enron in December 2001, prompted ongoing scrutiny and investigations by Congress and the U.S. Securities and Exchange Commission (SEC). More recently, attention has focused on CRAs' role in the subprime lending crisis. For example, US Senate hearings held in September 2007 (US Senate 2007 investigated whether the precipitous credit rating downgrades of structured finance products reflected problems in the credit rating process.

[4] Frost (2007) provides detailed discussion of concerns raised about CRA disclosure practices and other widespread criticisms of the large CRAs following the accounting scandals of 2000–2002.

[5] Congress passed the Credit Rating Agency Reform Act of 2006 with the goal of improving rating quality. The Act instituted disclosure requirements for CRAs seeking treatment as Nationally Recognized Statistical Rating Organizations (NRSROs), and increased the SEC's regulatory oversight of these entities. Section I provides additional discussion.

[6] For discussion of the role of rating committees in issuing credit watches, see FitchRatings (2006). Fons, Cantor, and Mahoney (2002) note that Moody's normally requires a formal rating committee to place an issuer on the Watchlist, and a different rating committee to remove the issuer from the Watchlist (either by confirming or changing the existing rating). In addition, meetings with company management usually follow a watch action.

[7] As one example, Moody's makes the following statement in its application for registration as an NRSRO (Moody's, 2007): "Once a credit rating has been published, (Moody's) will monitor the credit rating, as deemed appropriate, on an ongoing basis and will modify the credit rating as necessary in response to changes in our opinion of the creditworthiness of the issuer or issue."

[8] CRAs' contracting roles include facilitating private contracting (such as the use of rating-based constraints in loan agreements) and regulation.

more likely to be cited as causes for watch actions than for rating changes. Consistent with Boot et al. (2006), we find that credit watches occur more often in response to a deterioration in credit quality. Consistent with the CRAs, information-supplying and contracting roles, we find that the likelihood of issuing a credit watch in advance of a rating change is positively associated with issuer size, credit quality, and multi-notch rating changes.

We show that issuers attempt to address the concerns that prompt Moody's down watches, especially when down watches result from poor operating performance, financial distress, or accounting and/or litigation problems. These results support the Boot et al. (2006) view that credit watches can be viewed as an implicit contracts between the issuer and the CRA where the issuer agrees to take the actions necessary to avoid the reduction of its credit rating. Consistent with the implication of the Boot et al. (2006) model, we find that down watches are less likely than up watches to indicate the direction of the subsequent rating change.

We show that credit watch actions are significant information events. We find that down and up watches are associated with mean cumulative abnormal returns (CARs) of −1.1% and 4%, respectively. Hence, our results do not support the Boot et al. (2006) view that all market participants can observe a change in credit quality (Boot et al. (2006) do note that a negative market reaction should be observed if the public signal about credit quality deterioration and the issuance of a down watch occur simultaneously.) In contrast to the Boot et al. (2006) prediction, we find no evidence that rating changes preceded by a down watch conveys more information than changes not preceded by a down watch, and no evidence that the market impact of a rating downgrade is negatively associated with the market impact of the preceding credit watch.

Our examination of Moody's press releases accompanying credit watch actions and rating changes provides important evidence on the reasons for credit watch actions. This qualitative information, along with quantitative data (as used in most prior research), allows us to conduct more powerful analyses of watch actions and the information content of credit watches.

The remainder of the paper is organized as follows. Section I discusses the role of credit watches. Section II presents data and descriptive statistics. Section III analyzes triggering events and underlying causes of watch actions. Section IV analyzes factors associated with watch actions. Section V addresses whether firms take remedial actions to address problems identified by CRAs in the credit watch and whether the ability of credit watches to predict future rating changes differs between down and up watches. Section VI provides further evidence on the connection between credit watches and subsequent ratings changes. Section VII presents the results of market impact analyses, and Section VIII provides a summary and concluding remarks.

I. The Role of Credit Watches

A credit watch is a rating action that indicates the potential direction of a rating change that might follow the resolution, usually within 90 days, of specific events and/or trends.[9] CRAs state that credit watches are triggered by: 1) discrete events such as mergers, acquisitions, restructuring, and company announcements of plans expected to affect credit quality and/or 2) trends in the

[9] Credit watches, like credit ratings, are issued both to issuers and to specific debt obligations. Watch actions related to specific debt obligations closely mirror those related to debt issuers, but at times are different due to their unique features (e.g., as related to protection of creditors). See Moody's (2004), S&P (2005), and FitchRatings (2005, 2007) for further discussion.

issuer's operations or financial strength, in its industry or regulatory environment, or in the macroeconomic climate of its country or region of operations (Keenan, Fons, and Carty, 1998; FitchRatings, 2007).[10]

As discussed below, we hypothesize that credit watches, like credit ratings, support CRAs' roles of supplying value-relevant information and facilitating contracting (through promoting ratings stability) in the capital markets. Boot et al. (2006) present a model in which the credit watch can be viewed as an implicit contract between the issuer and the CRA, where the issuer agrees to undertake necessary actions to mitigate the possible deterioration of its credit standing. Based on this model, Boot et al. (2006) make a number of empirical predictions regarding the causes and consequences of the credit watch. We provide empirical evidence on these predictions.

A. Credit Rating Agencies' Information-Supplying Role

The large CRAs perform an information-supplying role by gathering and analyzing information relevant for assessing credit quality, and making the results of their analysis widely available to investors, portfolio managers, financial analysts, and other market participants. Beaver, Shakespeare, and Soliman (2006) note that information supplied by CRAs is used for investment and valuation, and that CRAs' information-supplying role is separate from their contracting role.[11]

Holthausen and Leftwich (1986) and Hand, Holthausen, and Leftwich (1992) provide early evidence on the information-supplying role of credit watches. The sample period in both studies is the first 26 months that Standard and Poor's (S&P) issued credit watches. These findings may not apply to later periods when CRA credit watch procedures became more stable. Therefore, further analysis of some of the issues examined by Holthausen and Leftwich (1986) and Hand et al. (1992) is warranted.

B. Credit Rating Agencies' Contracting Role

A second role of the large CRAs is to facilitate contracting (which includes regulation). Rating-based constraints appear in loan agreements, bond covenants, and other financial agreements.[12] U.S. financial regulators and lawmakers also use credit rating-based criteria.[13]

Rating stability should make credit ratings more useful in contracting. Measures of rating stability include frequency of rating changes, frequency of large multi-notch rating changes, and frequency of rating reversals (rating actions in the opposite direction of a previous rating

[10] Credit outlooks are opinions regarding the likely direction of a rating over a longer time horizon. See, for example, Keenan et al. (1998) and FitchRatings (2005).

[11] Much research documents CRAs' information-supplying role in the context of credit rating changes. Norden and Weber (2004) summarize 17 studies that investigate the market response to credit rating announcements, including Holthausen and Leftwich (1986), Hand, Holthausen, and Leftwich (1992), and Dichev and Piotrosky (2001). Also see Jorion, Liu, and Shi (2005) and Beaver, Shakespeare, and Soliman (2006).

[12] Ratings are also used in institutional investors' in-house investment rules. For example, see Stevens (2005).

[13] The SEC created the nationally recognized statistical rating organization (NRSRO) concept in 1975 to designate agencies whose credit ratings could be used by broker-dealers to comply with the SEC's Net Capital Rule, which requires broker-dealers to deduct from their net worth certain percentages of the market value of their proprietary security positions when computing net capital (Frost, 2007). Refer to SEC (2009) for discussion of recent actions taken by the Commission with the goal of enhancing the usefulness of NRSRO disclosures and improving the credit rating process. Cantor and Packer (1994, 1997) summarize selected uses of credit ratings in U.S. regulation.

action), each measured over a specified period.[14] CRAs state that they change a letter rating only when fundamental credit risk changes (which, they argue, usually happens gradually). Transitory shocks that might affect a company's credit risk in the short term are given relatively little weight in credit analysis.[15]

Contracting costs can increase sharply when credit ratings stability is impaired. Rating changes (particularly downgrades) can precipitate costly contract renegotiations and force managers to adjust their portfolio mixes. A rating downgrade that is subsequently reversed causes higher costs than when the rating is unchanged.

CRAs can maintain rating stability and yet provide timely information to market participants through the judicious use of credit watches. We expect that CRAs issue down watches more frequently than up watches because CRAs are more likely to be criticized or sued for rating downgrades that were not preceded by a down watch than for rating upgrades that were not preceded by an up watch.

We hypothesize that credit watches enhance the use of credit ratings in contracting.[16] Specifically, we expect that credit watches are used to convey information about changes in an issuer's credit quality where possible rating reversals are relatively costly. For example, "fallen angel" rating changes (those that lower an issuer's credit rating from investment grade to noninvestment grade) impose greater contracting costs than within-investment grade rating downgrades. As a result, we expect to observe the frequent use of credit watches in advance of fallen angel rating changes, since the credit watch conveys information about lower credit quality without issuing an actual rating change, which would be costly to reverse. As discussed in the next section, the Boot et al. (2006) model of the role of credit ratings also provides a motive for CRAs to increase rating stability by using credit watches.

C. The Boot, Milbourn, and Schmeits "Focal Point" Model of Credit Ratings

Boot et al. (2006) suggest that CRAs not only disseminate credit information to market participants but also use a credit watch procedure when market and/or firm developments threaten to affect a credit rating. Specifically, they argue that the credit watch can be viewed as an implicit contract between the issuer and the CRA where the issuer agrees to take the actions necessary to prevent the possible lowering of its credit rating. Boot et al. (2006) suggest that after issuing a negative credit watch, the CRA can discuss with management specific actions necessary (such as related to the firm's financing plans) to avoid a rating downgrade. The CRA then monitors the firm's progress.

CRAs' role in promoting ratings stability also motivates the Boot et al. (2006) model. Boot et al. (2006) suggest that CRAs issue negative watches to give the firm a chance to remedy the credit deterioration, thus potentially avoiding a credit downgrade (which is costly due either to explicit debt covenants or implicit institutional constraints). However, in contrast to the model where credit ratings supply new information to the market, Boot et al. (2006) argue that the issuance of a credit watch as such should not convey information to the market (since the credit watch is an expected event).

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[14] A multi-notch rating change is a rating change of two or more notches. A notch is the difference between adjacent ratings.

[15] See Cantor and Mann (2003, 2006) for further discussion of rating stability.

[16] Hirsch and Bannier (2009) provide empirical evidence in favor of the hypothesis that the credit watch procedure allows rating agencies to enter into an implicit contract with the rated entity.

II. Data and Descriptive Statistics

We obtain issuer credit rating and watch data from Moody's Default Risk Service (DRS).[17] The DRS provides access to Moody's complete proprietary default database featuring data on rating actions (since 1921) and credit watch actions (since 1992).[18] Our analyses focus exclusively on issuer ratings, which are opinions on an issuer's ability to honor senior unsecured financial obligations and contracts (Moody's, 2004). The DRS provides access to credit histories for over 10,000 issuers. Our analyses use Moody's credit rating and watch action data for all issuers whose financial statement data are available in Compustat for 1992–2010. We analyze only those credit watches that are resolved during our study period. For information content tests, we additionally limit the sample to issuers whose equity returns data are available from the Center for Research in Security Prices (CRSP).

We control for the confounding effects of announcements made concurrently with credit watch and rating change announcements by deleting contaminated observations. We define a contaminated watch action or rating change as one that is accompanied by a price-relevant news item made public during the three calendar days surrounding the rating or watch action date. We code a news item as price-relevant if it is related to any of the 20 specific disclosure items (across six disclosure categories) listed in the SEC Form 8-K.[19] We used the Factiva database to search the *Dow Jones News Service*, *Wall Street Journal* (WSJ), *PR News wire*, and *Business Wire* for announcements related to each issuer during the event window.

Controlling for event window contamination is even more important in market response analyses of credit watches than in those of rating changes. This is because (as claimed by CRAs and supported by evidence in this study) discrete events announced in the media are more likely to trigger watch actions than rating changes. If not controlled for, event window contamination increases the likelihood of rejecting the null hypothesis (no information content) when the direction of the credit watch is consistent with the information content of the contaminating event. We find that 1,367 (45.7%) of the 2,990 watch actions and 2,245 (33.3%) of the 6,748 rating actions used in market response tests are contaminated. This relative frequency of contaminated rating actions is higher than the 23.6% reported by Jorion, Liu, and Shi (2005), and lower than the 42.7% reported by Holthausen and Leftwich (1986).[20,21]

[17] Consistent with several prior studies, we view the large rating agencies as relatively homogeneous (e.g., Dichev and Piotrosky, 2001; Beaver, Shakespeare, and Soliman, 2006), and select Moody's as our representative firm. Refer to Dichev and Piotrosky (2001) for detailed discussion. For supporting evidence, refer to Holthausen and Leftwich (1986), Jewell and Livingston (1998), and Norden and Weber (2004).

[18] The DRS database also contains three issuer credit watch actions made during 1991. These are not included in our analyses.

[19] The Form 8-K disclosure categories are: 1) information about the issuer's business and operations, 2) financial information, 3) securities and trading markets, 4) matters related to accountants and financial statements, 5) corporate governance and management, and 6) other material events and disclosures made in conformance with Regulation Fair Disclosure (Reg FD) (e.g., management forecasts of financial results).

[20] Holthausen and Leftwich (1986) and Hand, Holthausen, and Leftwich (1992) classify rating change observations for market response tests as contaminated if there is a story about the firm in the WSJ during days -1 to $+2$ surrounding the rating change date that contains information other than the rating change or credit watch announcement. These studies do not disclose the relative frequency of contaminated watch actions. Jorion, Liu, and Shi (2005) consider an observation to be contaminated if any firm-specific price-relevant information appears in the WSJ within a three-day window surrounding the rating change date.

[21] Dichev and Piotroski (2001) do not control for event window contamination in their short window return tests, probably because their study focuses on long window (not short window) analyses.

Table I. Chronological Description of Rating Action and Watch Action Frequencies

Panel A describes the samples of 10,790 issuer rating actions and 4,539 watch actions during 1992–2010, showing year-by-year frequencies of rating downgrades, rating upgrades, withdrawn ratings, and the total number of rating actions; and year-by-year frequencies of down watches, up watches, uncertain watches, and the total number of watch actions. Panel B presents total watch actions divided by total rating actions and down watch actions divided by rating downgrades for each year.

Panel A. Rating Action and Watch Action Frequencies by Calendar Year

	Rating Actions				Watch Actions			
Year	Downgrade	Upgrade	Withdrawn Rating	Total	Down Watch	Up Watch	Uncertain Watch	Total
1992	182	110	96	388	27	15	1	43
1993	141	149	102	392	44	39	3	86
1994	114	139	76	329	56	43	11	110
1995	175	161	58	394	51	64	8	123
1996	147	211	86	444	86	98	9	193
1997	166	254	96	516	93	86	12	191
1998	272	208	93	573	158	117	10	285
1999	670	211	104	985	180	127	23	330
2000	402	194	103	699	237	105	19	361
2001	602	186	145	933	274	99	4	377
2002	646	100	150	896	318	57	8	383
2003	365	152	136	653	218	139	2	359
2004	211	217	93	521	171	111	12	294
2005	229	262	104	595	127	75	7	209
2006	278	253	131	662	173	100	8	281
2007	228	205	106	539	186	70	3	259
2008	322	77	71	470	347	48	8	403
2009	359	88	62	509	156	25	5	186
2010	85	146	61	292	44	21	1	66
Total	5,594	3,323	1,873	10,790	2,946	1,439	154	4,539

(*Continued*)

Table I describes our samples of 10,790 rating actions and 4,539 watch actions. Panel A in Table I shows that 5,594 (51.8%) of the 10,790 rating actions are rating downgrades, 3,323 (30.8%) are rating upgrades, and 1,873 (17.4%) are rating withdrawals.[22] Panel A also shows that 2,946 (64.9%) of the 4,539 watch actions are down watches, 1,439 (31.7%) are up watches, and 154 (3.4%) are uncertain watches. Down watches comprise a greater proportion of total watches than up watches in 17 of the 19 years presented in the table. The larger proportion of down watches relative to up watches is consistent with the larger proportion of rating downgrades relative to upgrades.[23]

[22] A rating is withdrawn when Moody's removes that rating for an obligation/issuer on which it previously maintained a rating (Moody's, 2004).

[23] Panel A in Table I shows evidence of calendar year clustering. The relative frequencies of downgrades are substantially larger in 1999–2002 than in the other years. Similarly, Jorion, Liu, and Shi (2005), using ratings data from all three

Table I. Chronological Description of Rating Action and Watch Action Frequencies (*Continued*)

Panel B. Watch Action Frequency Divided by Rating Action Frequency by Calendar Year

Year	Total Watch Actions Divided by Total Rating Actions		Down Watch Actions Divided by Rating Downgrades	
1992	0.111		0.148	
1993	0.219	0.282	0.312	0.365
1994	0.334	Five year average	0.491	Five year average
1995	0.312	(1992–1996)	0.291	(1992–1996)
1996	0.435		0.585	
1997	0.370		0.566	
1998	0.497	0.424	0.588	0.491
1999	0.335	Five year average	0.270	Five year average
2000	0.516	(1997–2001)	0.592	(1997–2001)
2001	0.404		0.455	
2002	0.427	0.473	0.495	
2003	0.550	Four year average	0.597	0.614
2004	0.564	(2002–2005)	0.810	Four year average
2005	0.351		0.572	(2002–2005)
2006	0.424		0.622	
2007	0.481		0.816	
2008	0.857	0.471	1.078	0.694
2009	0.365	Five year average	0.435	Five year average
2010	0.226	(2006–2010)	0.518	(2006–2010)
Mean	0.410		0.537	

Panel B in Table I shows the ratio of the number of total watch actions to the number of total rating actions and the ratio of the number of down watch actions to the number of rating downgrades for each year. The results show that the relative frequencies of both total watches and down watches have increased over time. Specifically, the frequency of watch actions relative to the frequency of rating changes increased from 28.2% from 1992 to 1996 to 42.4% from 1997 to 2001, and to more than 47% during both the 2002–2005 and 2006–2010 periods (47.3% and 47.1%, respectively). The trend in the frequency of down watches relative to the frequency of rating downgrades is similarly striking, increasing from 36.5% from 1992 to 1996 to 49.1% from 1997 to 2001, and to more than 60% during both the 2002–2005 and 2006–2010 periods (61.4% and 69.4%, respectively).[24] About 74.4% (2,273) of the 3,055 rated companies in our sample are industrial (not shown in Table I). The remaining companies are distributed across the banking, finance, insurance, public utility, and securities sectors.

Panel A in Table II shows rating action frequencies partitioned by the type of rating action (down, up, and withdrawn) and the existence and type of prior watch (down, up, uncertain, and

major CRAs, show a higher proportion of downgrades relative to upgrades during those four years. These results are consistent with the weak economic conditions and greater number of defaults during that period. Holthausen and Leftwich (1986) also show evidence on calendar year clustering. They find that more than 40% of the rating downgrades in their 1977–1982 sample period occurred during 1982, which is the *last* year in a five-year "down" period (1978–1982).

[24] See Blume, Lim, and MacKinlay (1998) and Jorion, Shi, and Zhang (2009) for evidence on declining credit ratings over time.

Table II. Rating Action Frequencies, Watch Action Frequencies, and Credit Watch Durations

This table presents descriptive evidence on credit rating actions, watch actions, and watch durations using a sample of 10,790 rating actions and 4,539 watch actions from 1992 to 2010. Panel A shows rating action frequencies partitioned by type of rating action (down, up, and withdrawn) and existence and type of prior watch (down, up, uncertain, and no prior watch). Panel A includes only 3,246 of the 4,539 credit watches in the sample, since not all credit watches are resolved by rating downgrades, upgrades, or rating withdrawals. Panel B presents frequency data for the five types of watch resolution in the sample: rating upgrades, rating downgrades, rating withdrawals, rating confirmations, and watch continuations. Panel B includes only 3,246 of the 10,790 rating actions in the sample, since most of the rating actions are not preceded by watches. Panel C presents mean and median watch durations (number of calendar days between watch action and watch resolution) cross-classified by watch type and watch resolution type. Median watch durations are shown in parentheses.

Panel A. Rating Action Frequency Cross-Classified by Type of Rating Action and Type of Credit Watch at the Time of the Rating Action

	Type of Watch Action				
Type of Rating Action	**Down Watch**	**Up Watch**	**Uncertain Watch**	**No prior Watch**	**Total**
Down	1,984 (35.5%)	12 (0.2%)	40 (0.7%)	3,558 (63.6%)	5,594 (100%)
Up	24 (0.7%)	987 (29.7%)	17 (0.5%)	2,295 (69.1%)	3,323 (100%)
Withdrawn	61 (3.3%)	106 (5.7%)	15 (0.8%)	1,691 (90.3%)	1,873 (100%)
Total	2,069 (19.2%)	1,105 (10.2%)	72 (0.7%)	7,544 (69.9%)	10,790 (100%)

Panel B. Watch Action Frequency Cross-Classified by Type of Watch and Type of Watch Resolution

	Type of Watch Resolution					
Type of Watch Action	**Rating Downgrade**	**Rating Upgrade**	**Rating Confirmed**	**Rating Withdrawn**	**Continuation of Watch**	**Total Number of Credit Watches**
Down	1,984 (67.3%)	24 (0.8%)	442 (15.0%)	61 (2.1%)	435 (14.8%)	2,946 (100%)
Up	12 (0.8%)	987 (68.6%)	59 (4.1%)	106 (7.4%)	275 (19.1%)	1,439 (100%)
Uncertain	40 (26.0%)	17 (11.0%)	20 (13.0%)	15 (9.7%)	62 (40.3%)	154 (100%)
Total	2,036 (44.9%)	1,028 (22.6%)	521(11.5%)	182 (4.0%)	772 (17.0%)	4,539 (100%)

(*Continued*)

Table II. Rating Action Frequencies, Watch Action Frequencies, and Credit Watch Durations (*Continued*)

Panel C. Mean and Median Watch Duration by Watch Type and Watch Resolution Type

	Type of Watch Resolution					
Type of Watch Action	**Rating Downgrade**	**Rating Upgrade**	**Rating Confirmed**	**Rating Withdrawn**	**Continuation of Watch**	**Overall**
Down	96 (76)	180 (172)	139 (111)	153 (124)	44 (14)	97 (74)
Up	142 (83)	120 (95)	139 (100)	158 (138)	47 (12)	110 (85)
Uncertain	93 (70)	137 (97)	100 (103)	161 (157)	85 (63)	102 (85)
Overall	96 (76)	122 (96)	138 (107)	157 (139)	48 (15)	101 (77)

no prior watch). The table shows that 1,984 (35.5%) of the 5,594 rating downgrades are preceded by down watches and 987 (29.7%) of the 3,323 rating upgrades are preceded by up watches. Note that 3,558 (63.6%) of the 5,594 rating downgrades and 2,295 (69.1%) of the 3,323 rating upgrades are not preceded by any watch action at all.

Panel B in Table II shows frequency data for the five types of watch resolution in the sample: rating downgrades, rating upgrades, confirmations, rating withdrawals, and watch continuations.[25] Confirmations and watch continuations are not considered formal rating actions. A watch confirmation confirms that the existing rating is appropriate. A watch continuation is a temporary confirmation of the existing rating with a statement that the issuer is still on watch because the reasons that led to the watch are unresolved (Keenan et al., 1998).[26] The results show that the majority of watches are "accurate" in the sense that they indicate the direction of future rating actions. Specifically, 1,984 (67.3%) of the 2,946 down watches are followed by rating downgrades and 987 (68.6%) of the 1,439 up watches are followed by rating upgrades. These figures are similar to those reported in Holthausen and Leftwich (1986), suggesting that credit watch/rating change agreement has remained fairly stable during the past 25–30 years.

Panel C in Table II shows the mean and median watch durations (the number of calendar days between watch action and watch resolution) cross-classified by types of credit watches and watch resolutions. The results show that watch duration is relatively short when the watch resolution is in the direction indicated by the initial watch direction. For down watches, the mean duration (96 days) for rating downgrades is shorter than the mean durations for upgrades, confirmed ratings, and withdrawn ratings (180, 139, and 153 days, respectively). Likewise, for up watches, the mean duration of 120 days for rating upgrades is shorter than the mean durations for downgrades, confirmed, and withdrawn (142, 139, and 158 days, respectively).[27] The relatively short duration for concordant credit watch/rating change pairs suggests that CRAs take less time to change ratings in a previously-expected direction than in a direction not previously expected. The mean duration for watch continuations is shorter than that for the other four types of watch resolutions. This result is difficult to interpret because CRAs have said very little about why they issue watch continuations.

Finally, Panel C in Table II shows that the mean watch duration for rating downgrades is shorter than the corresponding figures for the other two types of rating action. Specifically, the mean watch duration for rating downgrades is 96 days, as compared with 122 and 138 days for rating upgrades and confirmations, respectively. This result suggests that rating agencies tend to resolve the uncertainty associated with credit quality more quickly after they issue down watches than for up watches.

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[25] Panel A in Table II includes only 3,246 of the 4,539 credit watches in the sample, since not all credit watches are resolved by rating downgrades, upgrades, or rating withdrawals. Panel B in Table II includes only 3,246 of the 10,790 rating actions in the sample, since most of the rating actions are not preceded by watches. Panel A shows relative frequencies of rating changes that are preceded by a watch and those that are not preceded by a watch. In contrast, Panel B highlights whether watches, *once they are issued*, are followed by actual rating changes in the predicted manner (i.e., in the same direction).

[26] Our decision to consider watch continuations as a type of resolution follows the classification used by the CRAs, and implicitly assumes that the act of making the continuation announcement provides information. To gauge the extent to which a continuation announcement signals that a rating is likely to be changed, we analyze the outcomes of 243 down watch/continuation observations. We find that 71% of the 98 down watch/continuations that were not followed by another continuation were followed by rating changes (53 rating downgrades and 17 rating upgrades). In contrast, only 26% (25) of the down watch/continuations were confirmed. This result suggests that a continuation announcement signals that a rating is more likely to be ultimately changed than confirmed.

[27] This result is in sharp contrast to Holthausen and Leftwich (1986), who report the mean credit watch duration of 61.7 days for the entire sample of 222 credit watches.

III. Triggering Events and Underlying Causes of Watch Actions

To shed light on the nature of credit watches, we analyze press announcements of Moody's watch actions obtained from the Moody's press release database available in the Dow Jones Factiva news service. Each announcement begins with a paragraph that explicitly states the reason(s) for issuing the credit watch. We first identify the "triggering event" related to each credit watch—either a discrete event or trend/condition. Discrete events refer to issuers' announced plans or events expected to affect credit quality, but which are not certain to take place and/or whose effect on credit quality is uncertain. Examples include acquisitions, mergers, restructuring (including asset sales), and becoming a target. Trends or conditions are ongoing developments in the issuer's operations or financial strength, in its industry or regulatory environment, or in the macroeconomic climate of its country or region of operation that might affect its credit quality. Refer to Exhibit 1 for further description of triggering events as well as underlying causes for credit watch actions (discussed below).

Moody's announcements also discuss the underlying causes for issuing a credit watch. The most common underlying causes for credit watches relate to financial performance (e.g., earnings and/or cash flows), leverage and balance sheet characteristics, acquisitions (announced by the issuer), announcements of the issuer being a target in an acquisition, a planned or pending merger, and restructuring-related developments. Less common underlying causes are included in the "other" category. These include financial restatements, delays in filing financial statements, regulatory uncertainties, legal issues, debt covenant violations, and other items (See Exhibit 1.)

Table III shows the results of our analysis based on the sample of 2,990 of the 4,539 credit watches used in market impact tests. Table III shows credit watch frequencies cross-classified by type of triggering event (discrete or trend), watch direction (up, down, or uncertain), and event window contamination (contaminated or noncontaminated). The table shows that 1,296 (59.2%) of the 2,191 credit watches for which Moody's announcements are available are triggered by discrete events.[28] This result is consistent with CRAs' description of credit watches as often being caused by sudden, unexpected developments, and with the Boot et al. (2006) credit ratings model. We find that 1,002 (77.3%) of the 1,296 watch actions triggered by discrete events are contaminated. This result is expected, since events significant enough to change an issuer's creditworthiness often attract media coverage.[29]

Table III also shows that 399 (60.4%) of the 661 up watches and 826 (57.2%) of the 1,444 down watches for which Moody's announcements are available are triggered by discrete events, indicating that up watches are more likely than down watches to be triggered by discrete events.[30] Large and roughly similar percentages of both up watches and down watches triggered by discrete events are contaminated (i.e., 75.8% of the down watches and 80.2% of the up watches). This result suggests that discrete events that trigger up watches and down watches are likely to be viewed as comparably newsworthy.

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[28] Moody's press releases are generally not available on Factiva for dates before October 24, 2000. As a result, we are unable to locate press releases for 799 of the 2,990 watch actions.

[29] To investigate the relation between contaminating announcements and Moody's stated reasons for watch actions, we examined 50 randomly selected contaminated credit watch observations for which Moody's press releases were available. We found that 43 of the 50 cases involved "discrete event" credit watches accompanied by a contaminating announcement of the same (or closely related) information.

[30] The difference is significant at the 1% level (Chi-squared test).

Table III. Analysis of Credit Watch Triggering Events Disclosed in Moody's Press Releases

This table presents credit watch frequencies cross-classified by triggering event (discrete vs. trend), direction of watch (up, down, uncertain), and event window contamination (contaminated, noncontaminated). The sample analyzed consists of the 2,990 credit watches used in stock price tests. We define a contaminated watch action as one that is accompanied by a price-relevant news item published at some point during the three calendar days surrounding the rating or watch action date. We code a news item as price-relevant if it is related to any of the 20 specific disclosure items listed in the SEC Form 8-K. The Form 8-K disclosure categories are: 1) information about the issuer's business and operations, 2) financial information, 3) securities and trading markets, 4) matters related to accountants and financial statements, 5) corporate governance and management, and 6) other material events and disclosures made in conformance with Regulation FD (e.g., management forecasts of financial results).

	Triggering Events Disclosed in Moody's Press Release				
Direction of Watch	Discrete Events	Issuer or Environmental Trends	Subtotal	Not Known (Moody's Press Releases Not Available for Periods Before Oct. 24, 2000)	Total
Down watch					
Contaminated	626	170	796	82	878
Noncontaminated	200	448	648	385	1,033
Total down watch	826	618	1,444	467	1,911
Up watch					
Contaminated	320	56	376	45	421
Noncontaminated	79	206	285	257	542
Total up watch	399	262	661	302	963
Uncertain watch					
Contaminated	56	7	63	5	68
Noncontaminated	15	8	23	25	48
Total uncertain watch	71	15	86	30	116
All watch types					
Contaminated	1,002	233	1,235	132	1,367
Noncontaminated	294	662	956	667	1,623
Total watches	1,296	895	2,191	799	2,990

A question of interest is how Moody's learned about the discrete events that triggered the 294 noncontaminated discrete-event credit watches. If there was no news story near the announcement of the credit watch, how did Moody's learn about the event? Was the event known to the public before the start of the three-day window, or did Moody's learn about it from the company or some other source? We conduct a diagnostic analysis using Factiva to address the above questions. Specifically, we examine 50 randomly selected cases of noncontaminated watch actions triggered by discrete events. We identify discrete events for 45 of the 50 cases, all but one of which are company announcements.[31] The mean (median) number of calendar days between the discrete event announcement and the watch date is 18.6 (8). Seventeen of the 45 cases involved announcements of earnings and/or other types of financial results. Nine cases involved acquisition announcements, and the remaining 19 cases involved other types of news

[31] The exception was an issuer's technical default announced in a Moody's press release two days before the watch date.

(restructuring, debt, sale of a business, bankruptcy, regulatory events, etc.). This result, combined with the finding of significantly negative CARs associated with the noncontaminated down watches (discussed in Section VII and shown in Panel B in Table VII) confirms CRAs' superior skill in interpreting public announcements.

Table III also shows that relatively small proportions of the credit watches triggered by issuer or environmental trends are contaminated. Specifically, 170 (27.5%) of the 618 down watches, and 56 (21.4%) of the 262 up watches triggered by environmental trends are contaminated.

Table IV presents an analysis of triggering events and underlying causes related to both watch actions and ratings changes as disclosed in Moody's press releases. Panel A in Table IV shows credit watch frequencies cross-classified by underlying cause for the credit watch, type of triggering event, and watch direction. The table shows systematic differences in underlying causes between up watches and down watches as well as between different types of triggering event. For example, the second and third columns from the left show that financial performance, leverage and balance sheet, acquisition, and "other reasons" are more strongly associated with down watches than with up watches, whereas most target and merger announcements are associated with up watches. Note also that 642 (53.8%) of the 1,192 underlying causes associated with the trends or conditions triggering event category are related to financial performance, whereas only 270 (16.4%) of the 1,648 causes associated with the discrete event category are associated with financial performance.

Panel B in Table IV presents descriptive evidence on 600 randomly selected rating changes for which Moody's press releases are available. Analysis of evidence in Panels A and B in Table IV reveals noteworthy differences between credit watch (Panel A) and rating change (Panel B) characteristics. For example, in contrast to credit watches, most of which are triggered by discrete public events, 472 (78.7%) of the 600 rating changes are associated with trends. In addition, acquisition, target, merger, and restructuring events are cited as causes for 29.4% of the watch actions, in contrast to only 14.0% in the case of rating changes.[32,33] Further differences are that a larger percentage of the underlying causes leading to credit watches is financial performance-related than is observed for the rating changes (32.1% vs. 21.1%), and a smaller percentage of the underlying causes leading to credit watches is leverage- and balance sheet-related than is observed for the rating changes (25.8% vs. 43.4%).

In summary, as compared with rating changes, credit watches are 1) more likely to be triggered by discrete events, 2) more likely to result from uncertainties related to acquisition, target, merger, and restructuring developments, 3) more likely to be caused by uncertainties related to financial performance, and 4) less likely to be caused by uncertainties related to leverage. This evidence has implications for the relationship between credit watches and subsequent rating changes, and is discussed in Section VI.

IV. Factors Associated with Watch Actions

We expect that decisions to issue credit watches reflect CRAs' information-supplying and contracting roles. That is, CRAs are more likely to issue credit watches when demand for information is larger or when issuing a watch promotes rating stability. Since we expect that many factors associated with CRAs' contracting role are also associated with their information-supplying role, it is difficult to test these roles separately. As a result, we test the joint hypothesis

[32] 29.4% = (313 + 306 + 132 + 83) divided by 2,840, as shown in the right-hand column in Table IV, Panel A.

[33] 14.0% = (63 + 13 + 8 + 60) divided by 1,028, as shown in the right-hand column in Table IV, Panel B.

Table IV. Analysis of Triggering Events and Underlying Causes Related to Watch Actions and Rating Changes as Disclosed in Moody's Press Releases

This table presents credit watch (Panel A) and rating change (Panel B) frequencies cross-classified by 1) reason for the credit watch or rating change (financial performance, leverage, acquisition, merger, etc.), 2) type of triggering event (discrete vs. trend), and 3) watch or rating change direction (up, down, uncertain). The sample analyzed consists of 2,191 credit watches (the 2,990 credit watches used in stock price tests minus the 799 watches for which Moody's press releases are not available) and a randomly selected sample of 600 rating changes. The total credit watch frequencies presented in Panel A are larger than the Table III frequencies because many credit watches have multiple underlying causes. Similarly, the total reasons presented in Panel B exceed 600.

Panel A. Credit Watch Actions: Reasons for Watch Actions Cross-Classified by Triggering Events

	Triggering Events								Total			
	Discrete Events Watch Direction				Trends or Conditions Watch Direction				Watch Direction			
Underlying Cause for Watch	Down	Up	Uncert	Total	Down	Up	Uncert	Total	Down	Up	Uncert	Total
Financial Performance	222	43	5	270	422	216	4	642	644	259	9	912
Leverage and Balance Sheet	293	78	18	389	245	95	5	345	538	173	23	734
Acquisition	248	43	8	299	10	3	1	14	258	46	9	313
Target	91	173	36	300	0	5	1	6	91	178	37	306
Merger	40	80	5	125	2	4	1	7	42	84	6	132
Restructuring	42	17	4	63	13	6	1	20	55	23	5	83
Other Reason	141	47	14	202	130	22	6	158	271	69	20	360
Total	1,077	481	90	1,648	822	351	19	1,192	1,899	832	109	2,840

Panel B. Rating Changes: Reasons for Rating Changes Cross-Classified by Triggering Events

			Total (Discrete Events and Trends Combined)		
	Discrete Events (128 Rating Changes)	Trends (472 Rating Changes)	Rating Down (405 Rating Changes)	Rating Up (195 Rating Changes)	All Rating Changes (600 Rating Changes)
Financial Performance	32	185	70	147	217
Leverage and Balance Sheet	98	348	331	115	446
Acquisition	22	41	54	9	63
Target	12	1	9	4	13
Merger	5	3	3	5	8
Restructuring	26	34	51	9	60
Other Reason(s)	46	175	194	27	221
Total	241	787	712	316	1,028

that CRAs' decisions to issue credit watches are associated with both their information-supplying and contracting roles.

We use regression analysis to examine factors associated with the CRA's decision to issue a credit watch in advance of a credit rating change. We include in our analysis only those rating changes that resolve credit watches in the indicated direction, and separately examine rating downgrades, rating upgrades, and rating downgrades and upgrades combined.[34] Our regression model for rating downgrades is shown below (all variables and data sources are as described in Exhibit 2):

$$\begin{aligned} DnRateWthWatch_i = {} & \beta_1 + \beta_2 TotalAssets_i + \beta_3 MultiNotch_i + \beta_4 FallAngel_i + \beta_5 ToDefault_i \\ & + \beta_6 RegIndustry_i + \beta_7 A_i + \beta_8 Baa_i + \beta_9 Ba_i + \beta_{10} Caa_i + \beta_{11} RateDays_i \\ & + \beta_{12} AbsROA_i + \beta_{13} CostDebt_i + YearDummies + \varepsilon_i, \end{aligned} \tag{1}$$

where, for rating change *i*,

DnRateWthWatch = Indicator variable that equals one if a rating downgrade is preceded by a credit watch, and zero if the downgrade is not preceded by a watch;
TotalAssets = Natural logarithm of issuer's total assets (millions $US);
MultiNotch = Indicator variable that equals one for rating changes greater than one notch, and zero otherwise. A notch is the difference between adjacent ratings (where a rating consists of the generic rating category (e.g., Aa) including numerical modifiers (1, 2, and 3));
FallAngel = Indicator variable that equals one for fallen angels (i.e., issuers downgraded from investment to noninvestment grade), and zero otherwise;
ToDefault = Indicator variable that equals one for rating downgrade to default grade (Caa, Ca, and C rating categories), and zero otherwise;
RegIndustry = Indicator variable that equals one for firms in the public utility and finance industries, and zero otherwise;
A, Baa, Ba, Caa = Indicator variables for broad credit rating in effect immediately preceding a rating or watch action (*A* equals 1 for rating category A, and 0 otherwise; Baa equals 1 for rating category Baa, and 0 otherwise; *Ba* equals 1 for rating category Ba, and 0 otherwise; and Caa equals 1 for rating categories Caa, Ca, and C, and 0 otherwise);
RateDays = Number of calendar days between current rating change date and the prior rating change date;
AbsROA = Absolute value of return on assets (*ROA*), where *ROA* is defined as net income before extraordinary items divided by beginning-of-year total assets; and
CostDebt = Interest expense divided by the sum of short-term and long-term debt.

We expect all of the independent variables in Regression Model (1) to be associated with demand by external parties for information and thus *DnRateWthWatch*. Specifically, *TotalAssets* is a proxy for issuer size, and investor interest (and demand for information) is positively associated with

[34] Holthausen and Leftwich (1986) and Hand et al. (1992) use similar approaches. Specifically, Holthausen and Leftwich (1986) include in their analysis only rating changes that resolve credit watches in the indicated direction, and both Holthausen and Leftwich (1986) and Hand et al. (1992) separately examine rating downgrades and upgrades.

issuer size. We also conjecture that *MultiNotch*, *FallAngel*, and *ToDefault* are positively associated with investor interest and thus *DnRateWthWatch*, due to the relatively large valuation implications of these types of rating changes. We expect a positive association between *DnRateWthWatch* and *RegIndustry* due to the demand for information by regulators and investors. We expect negative regression coefficients on *A, Baa, Ba,* and *Caa* since investors in low credit-quality companies may be relatively sophisticated and less reliant on CRAs for information. We include *CostDebt* in the regression model as an additional measure of credit quality.

We expect *RateDays* (a proxy for rating change frequency) to be negatively associated with *DnRateWthWatch*. In other words, rating changes that are made less (more) frequently are more (less) likely to be preceded by a watch. Such an association would be consistent with a greater demand for credit watch information related to issuers that receive rating changes infrequently. The variable *AbsROA* captures uncertainty in predicting earnings (assuming that earnings are an important input to credit rating decisions). Relatively extreme earnings realizations are more transitory and therefore harder to predict. Thus, we expect a greater investor demand for credit watch information related to high *AbsROA* issuers.

As noted earlier, CRAs' decisions to issue credit watches also probably reflect their role as facilitators of contracting activity. In this regard, *Multinotch, FallAngel*, and *ToDefault* are expected to be positively associated with *DnRateWthWatch*, since the potential impairment of rating stability is greater for these types of rating changes.

We also estimate a rating upgrade regression model that closely resembles the rating downgrade model except that the dependent variable is *UpRateWthWatch* rather than *DnRateWthWatch*, *RiseStar* is used instead of *FallAngel*, and *FromDefault* is used instead of *ToDefault*. The model that includes both rating downgrades and rating upgrades includes both *FallAngel* and *RiseStar*, and *ToDefault* and *FromDefault*. The dependent variable in this third model is *BothRateWthWatch*, an indicator variable that equals one if a rating upgrade or downgrade is preceded by a credit watch, and zero otherwise. To determine whether the likelihood of issuing a credit watch is different for rating downgrades and upgrades, in the third regression model we include an indicator variable (*RateDown*) that equals one for rating downgrade and zero otherwise. Exhibit 2 presents definitions of all regression variables.

Table V shows the regression results. We use winsorized variables in all regressions.[35] Since the dependent variable is a 0/1 categorical variable, the assumptions of the ordinary least squares (OLS) method are violated. We therefore present the results of both the OLS and binary logit regressions (Long, 1997). Panel A presents the results of Regression Model (1). The results show that the adjusted R^2 of the OLS regression is 0.16, and both the F-statistic on the OLS regression and the Wald test on the binary logit regression are highly significant.[36] Because the results of the OLS and binary logit regressions are qualitatively similar, our discussion focuses on the OLS results for convenience.

Panel A shows that the estimated coefficient on *TotalAssets* is positive and significant at the 1% level (two-sided tests throughout this section), suggesting that CRAs are more likely to issue watches for larger firms. The estimated coefficient on *CostDebt* is negative and significant at the 1% level. Estimated coefficients on rating indicator variables (*Baa, Ba,* and *Caa*) are negative and

[35] All variables are 98% winsorized as follows: the bottom 1% of the values are set equal to the value corresponding to the 1st percentile while the upper 1% of the values are set equal to the value corresponding to the 99th percentile.

[36] Table V shows that 5,284 and 2,946 observations are used in the analyses using rating downgrades and upgrades, respectively. The reduction in sample sizes from the 5,594 downgrade and 3,323 upgrade observations shown in Table I is due to the fact that Compustat data items required for estimation are not available for all cases.

Table V. Factors Associated with Propensity to Issue Credit Watches

This table presents results from OLS and Logit regression estimations using rating downgrades only (Panel A, 5,284 observations), rating upgrades only (Panel B, 2,946 observations), and rating upgrades and downgrades combined (Panel C, 8,230 observations). The estimation model for rating downgrades is shown below.

$$\begin{aligned} DnRateWthWatchi = & \beta_1 + \beta_2 TotalAssets_i + \beta_3 MultiNotch_i + \beta_4 FallAngel_i + \beta_5 ToDefault_i \\ & + \beta_6 RegIndustry_i + \beta_7 \mathrm{Ai} + \beta_8 Baa_i + \beta_9 Ba_i + \beta_{10} Caa_i + \beta_{11} RateDays_i \\ & + \beta_{12} AbsROA_i + \beta_{13} CostDebt_i + YearDummies + \varepsilon_i, \end{aligned}$$

where, for rating change i, *DnRateWthWatch* = Indicator variable that equals one if a rating downgrade is preceded by a credit watch, and zero if the downgrade is not preceded by a watch; *TotalAssets* = Natural logarithm of issuer's total assets (millions of $US); *MultiNotch* = Indicator variable that equals one for rating changes greater than one notch, and zero otherwise; *FallAngel* = Indicator variable that equals one for fallen angels (issuers downgraded from investment to noninvestment grade), and zero otherwise; *ToDefault* = Indicator variable that equals one for rating downgrade to default grade (Caa, Ca, and C rating categories), and zero otherwise; *RegIndustry* = Indicator variable that equals one for firms in the public utility and finance industries, and zero otherwise; A, *Baa*, *Ba*, *Caa* = Indicator variables for broad credit rating in effect immediately preceding a rating or watch action (*A* equals 1 for rating category A, and 0 otherwise; *Baa* equals 1 for rating category Baa, and 0 otherwise; *Ba* equals 1 for rating category Ba, and 0 otherwise; and *Caa* equals 1 for rating categories Caa, Ca, and C, and 0 otherwise); *RateDays* = Number of calendar days between current rating change date and the prior rating change date; *AbsROA* = Absolute value of *ROA*, where *ROA* is defined as net income before extraordinary items divided by beginning-of-year total assets; and *CostDebt* = Interest expense divided by the sum of short-term and long-term debt. See Exhibit 2 for further information and data sources. The rating upgrades-only regression model (Panel B) closely resembles the rating downgrade model except that 1) the dependent variable is *UpRateWthWatch* rather than *DnRateWthWatch*, 2) *RiseStar* is used instead of *FallAngel*, and 3) *FromDefault* is used instead of *ToDefault*. The model that includes both rating downgrades and upgrades (Panel C) includes both *FallAngel* and *RiseStar*, and *ToDefault* and *FromDefault*. The t-statistic and Wald Chi-Square are used (in OLS and binary logit, respectively) to test for a significant difference between the estimated coefficient and zero, and are shown in parentheses. Table V shows that 5,284 and 2,946 observations are used in the analyses using rating downgrades and upgrades, respectively. The reduction in sample sizes from the 5,594 downgrade and 3,323 upgrade observations shown in Table I is due to the fact that Compustat data items required for estimation are not available for all cases. N denotes the number of observations.

Independent Variables	Panel A. Downgrades Only		Panel B. Upgrades Only		Panel C. Upgrades & Downgrades	
	OLS	Binary Logit	OLS	Binary Logit	OLS	Binary Logit
Intercept	−0.0434	−3.3714***	−0.0668	−4.4510***	−0.1029*	−3.9890***
	(−0.61)	(59.23)	(−0.65)	(25.15)	(−1.76)	(105.67)
RateDown					0.0653***	0.3657***
					(5.45)	(30.73)
TotalAssets	0.0300***	0.1503***	0.0344***	0.1924***	0.0320***	0.1657***
	(6.05)	(35.00)	(5.4)	(26.48)	(8.21)	(63.93)
MultiNotch	0.0992***	0.5003***	0.2006***	1.0795***	0.1344***	0.6983***
	(7.18)	(48.72)	(10.93)	(104.72)	(12.26)	(141.33)
FallAngel	−0.1353***	−0.6197***			−0.1379***	−0.7037***
	(−4.79)	(20.74)			(−5.52)	(31.79)

(*Continued*)

Table V. Factors Associated with Propensity to Issue Credit Watches(*Continued*)

Independent Variables	Panel A. Downgrades Only		Panel B. Upgrades Only		Panel C. Upgrades & Downgrades	
	OLS	Binary Logit	OLS	Binary Logit	OLS	Binary Logit
RiseStar			0.1862***	0.9890***	0.2227***	1.1240***
			(7.44)	(51.19)	(9.09)	(83.01)
ToDefault	−0.0386*	−0.1713*			−0.0598***	−0.2703***
	(−1.88)	(2.48)			(−3.13)	(6.76)
FromDefault			0.0058	0.2294	0.0052	−0.0321
			(0.13)	(0.47)	(0.15)	(0.02)
RegIndustry	0.0757***	0.3517***	0.0396**	0.2015***	0.0623***	0.3065***
	(4.53)	(18.38)	(2.01)	(3.38)	(4.88)	(22.39)
A	−0.0183	−0.1116	−0.0056	0.0253	−0.0210	−0.1167
	(−0.55)	(0.43)	(−0.08)	(0.01)	(−0.71)	(0.59)
Baa	−0.0846**	−0.4063***	−0.0745	−0.3028	−0.0898***	−0.4053***
	(−2.38)	(5.19)	(−1.15)	(0.79)	(−3.01)	(6.95)
Ba	−0.2642***	−1.2302***	−0.2122***	−1.0678***	−0.2565***	−1.2366***
	(−7.53)	(47.85)	(−3.22)	(9.33)	(−8.5)	(62.08)
Caa	−0.3140***	−1.4644***	−0.2938***	−1.7572***	−0.3214***	−1.5754***
	(−7.72)	(49.11)	(−3.93)	(15.35)	(−9.25)	(72.24)
RateDays	0.0000**	0.000078***	0.0000	0.0001	0.0000***	0.0001***
	(2.39)	(5.32)	(1.99)**	(3.16)	(3.33)	(9.69)
AbsROA	0.1497**	0.7781***	−0.1603	−1.2255***	0.0679	0.3811
	(2.15)	(4.56)	(−1.45)	(2.60)	(1.16)	(1.37)
CostDebt	−0.5763***	−3.5717***	−0.6965***	−4.4681***	−0.5531***	−3.4439***
	(−2.57)	(7.92)	(−3.03)	(8.49)	(−3.42)	(12.95)
F-value	34.57***		23.23***		51.02***	
Adjusted R^2	0.16		0.18		0.17	
Wald Statistic		739.74***		453.52***		1172.23**
N	5,284	5,284	2,946	2,946	8,230	8,230

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

significant at the 1% level and larger in absolute values for lower quality issuers. These results suggest that it is more likely for rating changes of relatively high-quality issuers to be preceded by credit watches, supporting the idea that investors in low credit-quality companies rely less on CRAs because they are more sophisticated than others. The estimated coefficient on *AbsROA* is positive and significant at the 5% level, supporting the idea that credit watches are more likely to be issued in cases of extreme profitability.

The estimated coefficient on *MultiNotch* is positive and significant at the 1% level, supporting the hypothesis that rating changes are more likely to be preceded by credit watches when they are large (i.e., more than a single notch). The estimated coefficient on *RegIndustry* is positive and significant, indicating that CRAs are more likely to issue watches to issuers operating in regulated industries. We find that the estimated coefficients on *FallAngel* and *ToDefault* are negative and significant. This result is inconsistent with the hypothesis that a credit watch is more likely for issuers that fall from investment grade to noninvestment grade or to the default grade. One interpretation of this result is that *FallAngel* and *ToDefault* companies fall out of investors' favor, reducing information demand for these companies. Consistent with our expectation, we find that the estimated coefficient on *RateDays* is positive and significant.[37]

Panel B in Table V shows the results of regressions that use the rating upgrade sample. As noted earlier, because we use the rating upgrade sample, we replace *FallAngel* and *ToDefault* with *RiseStar* and *FromDefault*. All other explanatory variables are the same as those used for the rating downgrade sample. The OLS F-statistic and the Wald statistic are both highly significant, and the OLS adjusted R^2 is 0.18. Estimated coefficients on *TotalAssets*, *Multinotch*, and *RiseStar* are all positive and significant at the 1% level. These results suggest that the propensity to issue a watch in advance of a rating upgrade is positively associated with issuer size and size of rating upgrade, and is relatively larger for rising star rating actions (i.e., from noninvestment to investment grade). As expected, estimated coefficients on rating indicator variables (*A, Baa, Ba,* and *Caa*) and *CostDebt* are all negative and significant, indicating that CRAs are more likely to issue watches for firms with higher credit ratings and lower cost of debt. Estimated coefficients on *RateDays*, *AbsROA*, and *FromDefault* are not significantly different from zero.

Panel C in Table V shows regression results using the entire sample of rating changes (i.e., 8,230 downgrades and upgrades). The positive regression coefficient on *RateDown* (significant at the 1% level) indicates that rating downgrades are more likely than rating upgrades to be preceded by watch actions. This result is consistent with our expectation that CRAs are more likely to issue down watches than up watches because rating downgrades that were not preceded by a down watch are more likely to be criticized or result in lawsuits than rating upgrades that were not preceded by an up watch. This result is also consistent with the prediction of Boot et al. (2006) that the CRA only considers imposing a credit watch if a bad signal has been observed. As expected, estimated coefficients on *TotalAssets*, *Multinotch*, *RiseStar*, and *RegIndustry* are also positive and significantly different from zero.

In summary, the strongest and most consistent results across the three regression models are that the propensity to issue credit watches in advance of rating changes is positively associated with issuer size, credit quality, large (multi-notch) rating changes, and rating downgrades.

In this section, we analyzed the likelihood of credit watches conditioned on future rating changes. The focus of our analysis was whether there was a preceding watch for a given rating change and the factors that explain this likelihood. As such, the analysis provided in this section does not shed any light on an important presumption of the Boot et al. (2006) model that credit watches prompt firms to attempt to fix the problem and its empirical implications. In the next section, we analyze the likelihood of rating changes conditioned on earlier watch actions to test the implication of the Boot et al. (2006) model.

V. Do Firms Take Remedial Actions to Address Problems?

As discussed in Section I.C, Boot et al. (2006) suggest that in the interval between a negative credit watch and a rating revision, CRAs discuss with management their financing plans and what they could do to avoid a downgrade. To shed some light on whether the Boot et al. (2006) model is descriptive, we analyze whether issuers attempt to address Moody's concerns during the down watch period.

[37] A final result (not shown in Table VI, Panel A) is that all of the 18 estimated 0/1 calendar year coefficients are significantly positive at the 1% level. Closely similar results are observed in Table V.

A. Credit Watches and Remedial Actions

We use the Factiva database to search news articles for 309 down watches in our study sample that Moody's subsequently confirmed.[38] We find that these news articles typically report Moody's concerns or corporate events that trigger Moody's decision to consider a downgrade, and then summarize what Moody's will focus on during its review. For rating confirmation news, these articles often give specific corporate actions which led to Moody's decision to confirm. The Moody's stated focus of review and later corporate actions allow us to determine whether issuers attempt (take actions) to address the situation or events that led to Moody's down watch.

Table VI shows the results of our analysis. As with the subsample of all 1,899 down watches shown in Table IV, most reasons for Moody's down watches that are subsequently confirmed can be classified into one of four broad categories: 1) merger, acquisition, or target announcements, 2) weak or declining financial performance, 3) leverage and balance sheet issues, and 4) other problems such as related to accounting problems and/or litigation issues. Refer to Exhibit 1 for further description of each category.

We search rating confirmation news from Factiva to determine whether issuers made concerted efforts to address Moody's concerns. We classify a confirmed down watch into the "Effort" category if such efforts were found. If the confirmation is due to reasons not attributable to issuer efforts, we classify it as "No effort." For example, Moody's issued a down watch for OMI Corporation due to the high leverage associated with an acquisition. However, later OMI's credit rating was confirmed because of Moody's belief that *"the cash flow that the acquired assets contribute to OMI's consolidated performance is adequate to maintain the company's credit fundamentals over the near term."* We classify this watch confirmation as "No effort" because cash flow generation from acquired assets does not result from any corrective action. Moody's simply didn't expect it when it placed OMI on a down watch. We classify a watch confirmation as "Grey" if the link between the confirmation and issuer actions exists but is not strong enough to attribute the confirmation to issuer efforts. We could not find rating action news for six confirmed down watches.

Panel A in Table VI shows that 142 (46%) of 309 confirmed down watches were prompted by merger and/or acquisition announcements, 66 (21.4%) were prompted by poor operating performance, 54 (17.5%) were due to financial distress, and 38 (12.6%) were associated with accounting problems and/or litigation issues. The results show that 162 (52.4%) of 309 confirmed down watches belong to the "Effort" category while 121 (39.2%) confirmed down watches belong to the "No effort" category. Among 142 confirmed down watches that were prompted by merger and/or acquisition announcements, 54 (38%) belong to the "Effort" category and 79 (55.6%) belong to the "No effort" category.) Of 66 confirmed down watches that were prompted by poor operating performance, 41 (62.1%) belong to the "Effort" category and 22 (33.3%) belong to the "No effort" category.) We find qualitatively similar results for the confirmed down watches associated with financial distress and accounting and litigation issues. We interpret these results as evidence that Moody's concerns were in general warranted and issuers attempted to address the issues that prompt Moody's down watches, especially for those down watches that were prompted by poor operating performance, financial distress, or accounting and/or litigation problems.

To better understand the remedial actions that firms take to address the issues that prompted Moody's down watches, we searched rating confirmation news from Factiva for the 88 down

[38] Note that the 442 down watch/confirmed observations shown in Table II are not the watch observations that we analyze in the subsequent tables. Panel B in Table II describes 4,539 watches. We use 2,990 watch observations in analyses presented in the remaining tables. These 2,990 watches include 1,911 down watches (see Table III) of which 309 are confirmed (not shown in any table).

Table VI. Reasons for Moody's Down Watches and Issuers' Actions During the Watch Period for Down Watches That Were Subsequently Confirmed

Panel A shows reasons for Moody's down watches and whether issuers attempted to address Moody's concerns using a sample of 309 down watch/confirmed observations. We classify a confirmed down watch into the "Effort" category if such efforts were found. If the confirmation is due to reasons not attributable to issuer efforts, we classify it into the "No effort" category. We classify a watch-confirmation into the "Grey" category if the link between confirmation and issuer actions is not strong enough to attribute confirmation to issuer efforts. We were unable to find rating action news for 9 confirmed down watches. Panel B presents the cross-tabulation of reasons for Moody's down watches cross-classified by the type of remedial (corrective) action taken by issuers for the 162 down watches that belong to the "Effort" category in Panel A. Note that the 442 down watch/confirmed observations shown in Table II are not the watch observations that we analyze in the subsequent tables. Table II, Panel B describes 4,539 watches. We use 2,990 watch observations in analyses presented in the remaining tables. These 2,990 watches include 1,911 down watches (see Table III) of which 309 are confirmed (not shown in any table).

Panel A. Moody's Down Watches and Whether Issuers Made Concerted Efforts to Address Moody's Concerns

	Reasons for Moody's Down Watches				
Issuer Actions	**Whole Sample**	**Merger, Acquisition, or Target**	**Financial Performance**	**Leverage and Balance Sheet**	**Other (Primarily Accounting Problems and/or Litigation Issues)**
Effort	162	54	41	43	24
No Effort	121	79	22	10	10
Grey	17	9	3	1	4
Unidentified	9	n/a	n/a	n/a	n/a
Total	309	142	66	54	38

Panel B. Moody's Down Watches Cross-Classified by the Type of Remedial (Corrective) Actions

	Reasons for Moody's Down Watches				
Types of issuer efforts (actions)	**Whole Sample**	**Merger, Acquisition, or Target**	**Financial Performance**	**Leverage and Balance Sheet**	**Other (Primarily Accounting Problems and/or Litigation Issues)**
Actions That Reduce Financial Risk	91	36	16	37	2
Actions That Improve Operating Income and/or Liquidity Profile	40	10	22	5	3
Actions That Resolve the Issuer's Accounting Problems	19	0	0	0	19
Statement of Intent to Address Moody's Concerns	12	8	3	1	0
Total	162	54	41	43	24

watches that belong to the "Effort" category. Close reading of rating confirmation news suggests that issuers' remedial actions can be grouped into the following four categories: 1) actions that reduce the issuer's financial risk, 2) actions that improve the issuer's operating income and liquidity profile, 3) actions that resolve the issuer's accounting problem, and 4) public statement by the issuer of its intent to address the issues raised by Moody's.[39, 40, 41]

Panel B in Table VI presents the cross-tabulation of reasons or events that trigger Moody's down watches by the type of remedial action taken by issuers. Of the 162 confirmations that involved issuers' corrective actions, 91 involved the issuer's actions to reduce its financial risk, 40 involved the issuer's actions to improve its operating income and liquidity profile, 19 involved actions to resolve the issuer's accounting problems, and 12 involved the issuer stating publicly its intent to address the issue raised by Moody's.

Not surprisingly, there is a close link between the reasons/events that prompted Moody's down watches and the actions taken by issuers. For example, 36 of the 54 confirmed down watches that were prompted by merger and/or acquisition announcements were followed by the issuer acting to reduce financial risk. This result should not come as a surprise because mergers and acquisitions frequently increase financial leverage. Confirmed down watches that were prompted by poor operating performance were followed by issuer actions to reduce financial risk (16 out of 41) or improve operating income (22 out of 41). The results also suggest that 37 of the 43 confirmed down watches that were prompted by financial distress were followed by the issuer actions to reduce financial risk. Finally, most of the confirmed down watches that were prompted by the issuer's accounting problems and/or litigation issues were followed by the issuer acting to resolve its accounting problems. We interpret these results as additional evidence that issuers often act during the credit watch period to directly address Moody's concerns. Overall, our results are consistent with the Boot et al. (2006) conjecture that a credit watch can be viewed as an implicit contract between the issuer and the CRA where the issuer agrees to take action to avoid the lowering of its credit rating.

B. Test of the Boot et al. (2006) Model

Boot et al. (2006) suggests that firms respond asymmetrically to down and up watches: firms take action after a down watch to avoid a downgrade, but do not act after an up watch. To the extent that firms' actions are successful, the Boot et al. (2006) model predicts that a down watch is less likely to be followed by a rating downgrade than an up watch to be followed by a rating upgrade.[42] We use the following regression model to test this prediction (all variables and data

[39] These actions encompass financing actions that aim to use proceeds to pay down debt or interest expense, including equity issuance (e.g., conversion of debt into equity), acquiring a new credit facility or term loan from the issuer's bank, spin-off of subsidiary or sale of assets, renegotiation with bank (e.g. extended maturity or waiver of default from the bank), and other efforts such as adopting a more conservative financing strategy and reducing or eliminating dividend payments.

[40] These actions include reducing costs and operating risk (e.g., terminating inefficient and risky projects and renegotiating with labor unions to achieve lower labor costs), changing business focus (e.g., making new business contracts which later generate large cash flows), and changing management.

[41] These actions include filing statements with the SEC by the date determined by Moody's and resolving accounting problems to reduce the cost of accounting control.

[42] We also expect to observe that down watches are less likely than up watches to indicate the direction of the subsequent rating change due to the CRA's expected conservatism. The CRA is not expected to issue an up watch *unless* it is highly confident, due to the high cost of "surprise" rating downgrades following an up watch.

sources are as described in Exhibit 2):[43]

$$\begin{aligned} WatchRateConcord_i = {} & \beta_1 + \beta_2 WatchDown_i + \beta_3 WatchDuration_i + \beta_4 RegIndustry_i \\ & + \beta_5 AbsROA_i + \beta_6 DiscreteEvent_i + \beta_7 FinanPerf_i + \beta_8 M\&A_i \\ & + YearDummies + \varepsilon i, \end{aligned} \tag{2}$$

where, for each observation i,

WatchRateConcord = Indicator variable that equals 1 if the indicated rating change occurs at the watch end date (down watch followed by rating downgrade or up watch followed by rating upgrade), and 0 otherwise;
WatchDown = Indicator variable that equals 1 for down watches, and 0 otherwise;
WatchDuration = Number of calendar days between watch start and end dates;
RegIndustry = Indicator variable that equals 1 for firms in the public utility and finance industries, and 0 otherwise;
DiscreteEvent = Indicator variable that equals 1 for a credit watch triggered by a discrete event (see Exhibit 1), and 0 otherwise;
FinanPerf = Indicator variable that equals 1 for a credit watch having a financial performance-related underlying cause (see Exhibit 2), and 0 otherwise;
M&A = Indicator variable that equals 1 for a credit watch having a merger, acquisition, or target-related underlying cause (see Exhibit 2), and 0 otherwise.

The Boot et al. (2006) model predicts that the sign of the regression coefficient (β_2) on *WatchDown* is negative. We also expect to observe greater agreement between watch actions and rating actions as the watch duration becomes shorter (i.e., rating actions occur nearer to the watch issue date). Thus, we expect a negative regression coefficient on *WatchDuration*. We expect that credit risk is easier to forecast in regulated industries (leading to a positive estimated coefficient on *RegIndustry*), but more difficult to forecast for extremely profitable and unprofitable issuers (leading to a negative coefficient on *AbsROA*). We include *DiscreteEvent*, *FinanPerf*, and mergers and acquisitions (*M&A*) to control for the possible effects of triggering events and underlying causes on the dependent variable.

Panel A in Table VII shows the results of Regression Model (2). Estimated coefficients on *WatchDown* are negative and statistically significant, indicating that a down watch is less likely to be followed by a rating downgrade than an up watch to be followed by a rating upgrade. This result is consistent with the Boot et al. (2006) model prediction that firms will take actions to avoid a downgrade after a down watch, but not take action after an up watch. Not surprisingly, we find that estimated coefficients on *WatchDuration* are also negative and significant, indicating that credit watches are more likely to indicate the direction of future rating changes as watch duration becomes shorter. However, estimated coefficients on *RegIndustry* and *AbsROA* are not significantly different from zero. The results also show that watches are more likely to indicate the direction of subsequent rating changes when the underlying cause of credit watches is financial performance.

[43] The analysis uses 3,500 credit watches/rating change pairs for the primary estimation model, and 3,166 credit watch/rating change pairs for the expanded model (discussed below). The analysis includes rating upgrades, rating downgrades, and rating confirmations.

Table VII. Credit Watch/Rating Change Agreement Analysis

This table presents results from an analysis of credit watch/rating change agreement—the extent to which the direction of credit watches indicates the direction of subsequent rating changes. The analysis involves estimating regression models in which the dependent variable equals 1 if the expected rating change occurs by the watch end date, and 0 otherwise. The analysis includes rating upgrades, rating downgrades, and rating confirmations. The estimation model is:

$$WatchRateConcord_i = \beta_1 + \beta_2 WatchDown_i + \beta_3 WatchDuration_i + \beta_4 RegIndustry_i + \beta_5 AbsROA_i + \beta_6 DiscreteEvent_i + \beta_7 FinanPerf_i + \beta_8 M\&A_i + YearDummies + \varepsilon_i,$$

where, for each observation *i*, *WatchRateConcord* = Indicator variable that equals 1 if the indicated rating change occurs at the watch end date (down watch followed by rating downgrade or up watch followed by rating upgrade), and 0 otherwise; *WatchDown* = Indicator variable that equals 1 for a down watch, and 0 otherwise; *WatchDuration* = Number of calendar days between watch start and end dates; *RegIndustry* = Indicator variable that equals 1 for firms in the public utility and finance industries and 0 otherwise; *DiscreteEvent* = Indicator variable that equals 1 for a credit watch triggered by a discrete event (see Exhibit 1), and 0 otherwise; *FinanPerf* = Indicator variable that equals 1 for a credit watch having a financial performance-related underlying cause (see Exhibit 1), and 0 otherwise; *M&A* = Indicator variable that equals 1 for a credit watch having a merger, acquisition, or target-related underlying cause (see Exhibit 2), and 0 otherwise; and all variables and data sources are as described in Exhibit 2. The analysis uses 3,500 credit watche/rating change pairs for the primary estimation model (panel A), and 3,166 credit watch/rating change pairs for the expanded model (Panel B). The *t*-statistic and Wald Chi-Square are used (in OLS and binary logit, respectively) to test for a significant difference between the estimated coefficient and zero, and are shown in parentheses. Additional variables presented in panel B: *A*, *Baa*, *Ba*, *Caa* = Indicator variables for broad credit rating in effect immediately preceding a rating or watch action (*A* equals 1 for rating category A, and 0 otherwise; *Baa* equals 1 for rating category Baa, and 0 otherwise; *Ba* equals 1 for rating category Ba, and 0 otherwise; and *Caa* equals 1 for rating categories Caa, Ca, and C, and 0 otherwise); *MultiNotch* = Indicator variable that equals one for rating changes greater than one notch, and zero otherwise; *CostDebt* = Interest expense divided by the sum of short-term and long-term debt. *N* denotes the number of observations.

Independent Variables	Panel A		Panel B	
	OLS	Binary Logit	OLS	Binary Logit
Intercept	1.1277***	5.1583***	1.1067***	4.7554***
	(19.94)	(25.08)	(13.79)	(16.35)
WatchDown	−0.1469***	−1.4255***	−0.1507***	−1.3801***
	(−11.19)	(100.64)	(−10.83)	(75.07)
WatchDuration	−0.0005***	−0.0038***	−0.0005***	−0.0043***
	(−8.53)	(67.14)	(−9.10)	(62.95)
TotalAssets			−0.0012	−0.0037
			(−0.27)	(0.01)
A			−0.0280	−0.2373
			(−1.04)	(0.63)
Baa			−0.0787***	−0.5660***
			(−2.89)	(3.57)
Ba			−0.1396***	−1.0441***
			(−4.97)	(11.49)
Caa			−0.1386***	−1.2734***
			(−3.95)	(11.62)

(*Continued*)

Table VII. Credit Watch/Rating Change Agreement Analysis (*Continued*)

Independent Variables	Panel A		Panel B	
	OLS	Binary Logit	OLS	Binary Logit
RegIndustry	0.0084	0.1074	0.0010	0.0178
	(0.66)	(0.88)	(0.07)	(0.02)
AbsROA	0.0120	0.0954	−0.0543	−0.6228*
	(0.41)	(0.12)	(−1.11)	(1.86)
CostDebt			0.0694	0.6397
			(0.68)	(0.27)
Multinotch			0.2100***	3.6979***
			(16.00)	(101.38)
ToDefault			0.0746***	1.5333***
			(2.73)	(5.78)
DiscreteEvent	−0.0491***	−0.4606***	−0.0463***	−0.4718***
	(−2.84)	(9.86)	(−2.66)	(8.39)
FinanPerf	0.0859***	0.8835***	0.0888***	0.8806***
	(6.11)	(42.81)	(6.19)	(34.21)
M&A	−0.0464**	−0.3175***	−0.0641***	−0.4703***
	(−2.17)	(3.67)	(−2.96)	(6.34)
F-value	17.93***		23.80***	
Adjusted R^2	0.108		0.192	
Wald Stat.		329.98***		374.00***
N	3,500	3,500	3,166	3,166

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

We also estimate an expanded credit watch/rating change agreement model that includes five additional independent variables used in Regression Model (1): *TotalAssets*, four rating indicator variables (*A, Baa, Ba,* and *Caa*), *CostDebt*, *Multinotch*, and *ToDefault*. We expect that variables associated with the CRAs' information-supplying role (and thus the demand for credit rating information) might also be associated with their incentives to issue "accurate" credit watches. Panel B in Table VII presents the results of the expanded regression model. The results show that the sign and statistical significance of the regression coefficients on *WatchDown* and *WatchDuration* are qualitatively identical to those in Panel A. The explanatory power (adjusted $R^2 = 0.192$) of the expanded model is higher than that (adjusted $R^2 = 0.108$) of Regression Model (2), and estimated coefficients on four (*Multinotch*, *Baa, Ba,* and *Caa*) of the eight additional variables are significantly different from zero at the 1% level. These results are consistent with the view that CRAs have greater incentives to provide accurate credit watches for firms with higher credit ratings and when expected changes in credit ratings are larger.

There is an alternative explanation for the negative coefficients on *Baa*, *Ba*, and *Caa*. Suppose that CRAs issue a down watch whenever the problem is potentially fixable, but not if the problem is unlikely to be fixed. Suppose also that issuers with lower ratings have a greater incentive to fix the problem to avoid rating downgrades. Unless issuers with lower ratings have a greater incentive than other issuers to attempt to ensure that an up watch is followed by a rating upgrade, credit watches are less likely to indicate the direction of the subsequent rating change for issuers with lower ratings.

VI. Connection between Credit Watches and Subsequent Rating Changes

As noted in Section II, a credit watch indicates the potential direction of a rating change that might follow the resolution of specific events and/or trends. We therefore expect to observe a close connection between credit watches and subsequent rating changes. Specifically, we expect that credit watches convey information about material uncertainties (typically triggered by a specific event) and that subsequent rating changes reflect changes in credit quality related to resolution of the uncertainty (often caused by a gradual change or trend). CRAs' press releases disclosing credit watch and rating actions should discuss such a connection.

A. Analysis of Aggregate Data

The aggregate data presented in Table IV are consistent with the expected connection between credit watches and subsequent rating changes. As shown in Table IV, credit watches, as compared with rating changes, are 1) more likely to be triggered by discrete events, 2) more likely to result from uncertainties related to acquisition, target, merger, and restructuring developments, 3) more likely to be caused by uncertainties related to financial performance, and 4) less likely to be caused by uncertainties related to balance sheet and leverage issues. This evidence is consistent with the following expected connections between credit watches and subsequent rating changes: 1) the typical credit watch is triggered by a discrete, publicly known event that leads to a material uncertainty related to credit quality and 2) the uncertainty is often resolved gradually. (For example, a "bad news" earnings announcement triggers a down watch. The issuer's deteriorating financial position gradually leads to increased leverage, which ultimately results in a ratings downgrade.) Evidence in Table IV is also consistent with another expected relation between credit watches and subsequent ratings changes: 1) an issuer announces a pending acquisition, merger, or restructuring development and 2) the development leads to a reduction (or increase) in credit quality that eventually leads to a rating change.

We also observe an explicit connection between credit watches and the subsequent rating change press releases. Our analysis of 600 Moody's press releases indicates that the CRA almost always refers specifically to the credit watch being resolved.

B. Analysis of Individual Credit Watch/Rating Change Sequences

Our interpretations of the aggregate data in Table IV are confirmed in an analysis of a sample of 30 credit watch/rating change pairs.[44] In 13 (43%) of the 30 cases, Moody's cited a specific event as the trigger for the watch and then cited general conditions as the reason for the rating change.[45] We find that in 9 of the 30 cases, a credit watch issued for financial performance-related reasons was followed by a leverage/balance sheet-related rating change. Thus, as expected, financial performance-related developments (which the CRA typically learns about in an issuer announcement such as an earnings release) often result in significant balance sheet-related changes over time. In all but two of the 30 credit watch/rating change pairs we observed an obvious connection between the reasons for credit watch and the subsequent rating change. For example, as reflected in the aggregate data shown in Table IV, credit watches caused by changes in financial

[44] We examine a relatively small sample due to the extensive time involved in locating and analyzing the credit watch/rating change pairs.

[45] Twenty four of the 30 observations were down watches followed by rating downgrades, and six of the observations were up watches followed by rating upgrades.

performance were often resolved by rating changes caused by related leverage/balance sheet deterioration or improvement. We also find that credit watches triggered by acquisition/target/merger announcements were often resolved by leverage-related rating changes. We interpret these results as evidence that the rating changes do generally reflect resolutions of conditions that triggered the preceding credit watch.

C. Analysis of the Boot et al. (2006) Prediction about Negative Watches and Baa-Rated Issuers

Boot et al. (2006) predict that a negative watch is more likely to be followed by a rating confirmation for Baa-rated issuers than for other issuers.[46] This prediction arises from the conjecture that the Baa-rated issuers are more likely than other issuers to take actions to avoid a rating downgrade because institutional investors often are allowed to invest only in highly-rated (i.e., investment grade) issuers.[47] Consistent with this prediction, we find that the relative frequency of credit rating confirmations following negative watches is larger in the Baa ratings subsample than in the non-Baa ratings subsample. Specifically, our results show that 87 (20.4%) of the 427 rating actions in the Baa subsample are rating confirmations whereas only 211 (15.6%) of the 1,353 rating actions in the non-Baa subsample are rating confirmations.

To formally test whether a ratings confirmation is more likely for Baa credit rating observations than for non-Baa credit rating observations, we estimate a binary logistic model (where the dependent variable equals one for a ratings confirmation, and zero for any other type of rating action) using the down watch observations only. We find that the estimated coefficient on the *Baa* indicator variable is significant with a p-value of 0.02, two-sided test. We also estimate a model which includes a reduced set of control variables (*LEV*, *ROA*, and *SIZE*) that may affect rating decisions. Results are similar to those using the model containing only the single *Baa* rating independent variable.

VII. Market Impact Analysis

In this section, we analyze the effects of credit watch and rating change announcements on stock returns using standard event study methodology to measure abnormal returns. We calculate abnormal returns using the coefficients of the standard market model estimated over days (−150, −46). We include only those observations that have at least 50 daily returns during the estimation period (−150, −46) and all three-day returns during the event period (−1, +1). As a result, the number of observations used in our market impact analysis is smaller than the corresponding numbers in the rating and watch analyses presented in Sections III.B and III.C.

We calculate the cross-sectional mean of the abnormal returns across the N_t issuers in each subsample on each event day t, and call it abnormal return (AR t) $= \Sigma_i \mathrm{AR}(i,t)/N_t$, where AR($i$,$t$) is the abnormal stock return of issuer i on day t). We then sum the mean abnormal returns across the return window to calculate the cumulative abnormal return (CARτ) $= \Sigma_\tau \mathrm{AR}(t)$, where Σ_τ denotes the summation over $t = \upsilon$ through τ, where υ and τ are, respectively, the beginning and

[46] Credit ratings below Baa (Moody's) and BBB (S&P and FitchRatings) are considered to be noninvestment grade ("junk" grade).

[47] Boot et al. (2006) predict that the likelihood of being put on credit watch is nonmonotonic in the credit quality of the firm. The likelihood is small for low or high quality firms since the credit watch procedure is either unlikely to be effective or redundant for these firms, and large for intermediate quality firms because the credit watch procedure is likely to be most effective for these firms.

ending day of each CAR(τ) calculation). We report results for three-day CARs (i.e., the event period $(-1, +1)$).[48]

A. Market Reaction to Credit Watch Announcements

In this section, we provide further empirical evidence on the price impact of credit watches. The Boot et al. (2006) model assumes that all market participants can observe changes in credit quality that lead to credit watches, and thus credit watch announcements do not affect share prices. Boot et al. (2006) predict that the market reacts negatively only if the public signal about credit quality deterioration and the issuance of a down watch occur simultaneously.

Table VIII shows the three-day mean CARs surrounding watch start dates cross-classified by the direction of watches (up, down, uncertain), the type of triggering events (discrete events vs. trends), and underlying causes (financial, *M&A*-related, and other).[49] Panel A shows the results using all watch observations during our study period and Panel B shows the results using only noncontaminated observations.

Panel A shows several noteworthy results. First, using a larger sample and a longer and more recent time period than has been used previously, we present strong evidence that credit watch actions are significant information events. We find that down and up watches are associated with mean CARs of −1.1% and 2.4%, respectively. It is interesting to note that the mean CAR is significant and positive (2%) for uncertain watches (i.e., watches that do not specify the likely direction of future rating change). The results also show that the mean CARs for down watches are similar across triggering events whereas the mean CARs for up watches are quite different across triggering events. For example, the mean CAR for up watches that are triggered by discrete events is 4.3%, whereas the mean CAR for up watches that are triggered by issuer trends (e.g., in financial performance) is 0.4%.

Panel B shows that noncontaminated down and up watches are associated with mean CARs of −1.1% and 0.8%, respectively. Thus, the market response to down watches is robust to the deletion of contaminated observations. The response to up watches, although smaller than the market response for the full sample, remains highly significant. These results indicate that, contrary to Boot et al.'s (2006) view, the credit watch announcements carry new information on credit quality even when they do not accompany other public signals. In addition, the mean CAR associated with noncontaminated down watches is negative and highly significant in all partitions with the exception of the *M&A*-related underlying cause partitions. In contrast, CARs in many of the up watch partitions do not remain significantly positive. Similarly, fewer mean CARs in the uncertain watch partitions are significantly different from zero after removal of contaminated observations.[50]

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[48] We find qualitatively similar results regardless of whether we use the CRSP value-weighted or equal-weighted returns for the market return. We report the results using the value-weighted return. We find similar results when we use the $(0, +1)$ return window. The $(-1, 0)$ return window yields slightly smaller CARs than those from the $(-1, +1)$ return window. One possible conjecture from these results is that many credit watches may be released after the market close. We are unable to test this conjecture, however, because information on the exact time when credit watch announcements are released is not available. We use 98% winsorized variables in all CAR analyses. This approach yields conservative estimates of market response, and as a result, comparisons between our results and those from analyses of nonwinsorized abnormal returns should be made with caution.

[49] The *M&A*-related category includes the following underlying causes: acquisition, target, and merger. See Exhibit 1.

[50] It is reasonable to expect that removal of contaminated observations has a greater effect on up watches than on down watches. Recall that up watches are more likely than down watches to be precipitated by discrete events, and that credit watches precipitated by discrete events are more likely to be contaminated. (See Table III.) If the information conveyed by discrete events (that precipitate credit watches) is highly correlated with the information conveyed by credit watch

Table VIII. CARs Surrounding Watch Start Dates

This table presents three-day CARs surrounding credit watch issue dates during 1992–2010 cross-classified by direction of watch (up, down, uncertain), type of triggering event (discrete event vs. trend) and underlying cause (financial, *M&A*-related [acquisition, target, and merger-related], and other). All analyses use 98% winsorized variables. Panel A shows the results using all watch observations during our study period and Panel B shows the results using only noncontaminated observations. Abnormal returns are calculated by using the coefficients of the standard market model estimated over days (−150, −46), where CRSP value-weighted returns are used for the market return. We include only observations that have at least 50 daily returns during the estimation period (−150, −46) and all three-day returns during the event period (−1, +1). As a result, the number of observations in the market impact tests is smaller than in the rating and watch analysis. We calculate the cross-sectional mean of the abnormal returns across the N_t issuers in each subsample on each event day t, and call it $\text{AR}(t) = \Sigma_i \text{AR}(i,t)/N_t$. We then sum the abnormal returns across the return window to calculate the across-time summation of AR(t), and call it $\text{CAR}(\tau) = \Sigma_\tau \text{AR}(t)$, where Σ_τ denotes the summation over $t = \upsilon$ through τ, where and τ are, respectively, the beginning and ending day of each CAR(τ) calculation. We report results for three-day CARs (trading days (−1, +1) surrounding day 0).

Panel A. All Observations (Contaminated and Noncontaminated)

	By Triggering Event				By Triggering Event Cross-Classified by Underlying Cause					
					Underlying Cause is Financial		Underlying Cause is *M&A* Related		Other Causes	
	Discrete Event	Trend	No Moody's PR	Total	Discrete Event	Trend	Discrete Event	Trend	Discrete Event	Trend
Down Watch										
CAR	−0.007***	−0.016***	−0.013***	−0.011***	−0.011***	−0.017***	0.019***	−0.001	−0.021***	−0.015***
(t-stat.)	(−5.34)	(−6.85)	(−5.42)	(−11.37)	(−6.01)	(−6.78)	(10.02)	(−0.06)	(−7.48)	(−3.00)
Number of observations	826	618	467	1,911	482	551	377	12	180	137
Up Watch										
CAR	0.043***	0.004*	0.016***	0.024***	0.032***	0.003	0.051***	0.026*	0.023***	0.008
(t-stat.)	(21.57)	(1.73)	(7.13)	(18.14)	(7.39)	(1.39)	(21.94)	(2.14)	(5.54)	(1.33)
Number of observations	399	262	302	963	108	246	296	12	64	26
Uncertain Watch										
CAR	0.031***	−0.042***	0.025***	0.02***	0.016	−0.046*	0.051***	−0.0362	−0.019**	−0.042**
(t-stat.)	(4.90)	(−2.68)	(3.14)	(4.22)	(1.34)	(−1.78)	(6.49)	(−0.93)	(−2.03)	(−2.17)
Number of observations	71	15	30	116	21	7	47	3	18	7
Total number of observations	1,296	895	799	2,990	611	804	720	27	262	170

(*Continued*)

Table VIII. CARs Surrounding Watch Start Dates (*continued*)

Panel B. Noncontaminated Observations

	By Triggering Event				By Triggering Event Cross-Classified by Underlying Cause					
					Underlying Cause is Financial		Underlying Cause is *M&A* Related		Other Causes	
	Discrete Event	Trend	No Moody's PR	Total	Discrete Event	Trend	Discrete Event	Trend	Discrete Event	Trend
Down Watch										
CAR	−0.007**	−0.012***	−0.012***	−0.011***	−0.009***	−0.011***	0.007	−0.0039	−0.015***	−0.016***
(*t*-stat.)	(−2.40)	(−4.39)	(−4.94)	(−6.88)	(−2.64)	(−4.10)	(1.56)	(−0.25)	(−2.88)	(−2.56)
Number of observations	200	448	385	1,033	133	409	50	9	61	90
Up Watch										
CAR	0.009**	0.001	0.014***	0.008***	0.015*	0.001	0.008	−0.00454	0.004	0.0053
(*t*-stat.)	(1.93)	(0.36)	(5.79)	(4.95)	(1.73)	(0.48)	(1.28)	(−0.37)	(0.37)	(0.79)
Number of observations	79	206	257	542	28	196	43	6	17	22
Uncertain Watch										
CAR	0.01	−0.045**	0.02**	0.006	0.034	−0.031	0.004	−0.08945	−0.001	−0.0519**
(*t*-stat.)	(0.71)	(−2.28)	(2.34)	(0.88)	(0.95)	(−0.85)	(0.28)	(−1.09)	(−0.05)	(−2.00)
Number of observations	15	8	25	48	5	3	8	1	4	5
Total number of observations	294	662	667	1,623	166	608	101	16	82	117

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Overall, our results do not support the view of Boot et al. (2006) that credit watches are noninformational events because the change in credit quality is observable to all market participants. Our results are consistent with the findings of Holthausen and Leftwich (1986), Hand et al. (1992), Hull, Predescu, and White (2004) and Micu, Remolona, and Wooldridge (2006) that credit watches are significant information events.

Table IX presents the results of a regression model where the three-day CAR surrounding the watch start date is the dependent variable, and independent variables include indicator variables representing different watch action/rating direction combinations (i.e., *WtchDnRatUp* and *WtchDnRatDn* for down watches, and *WtchUpRatUp* and *WtchUpRatDn* for up watches), *TotalAssets*, *postFD, InvestGrade, WatchDuration*, *Multinotch, ConcEvent*, *FinanPerf*, and *M&A*.[51] We include the indicator variables representing different watch action/rating direction combinations to test whether the market reaction around the watch start date varies with the ultimate outcome of the watch. We include the *postFD* dummy variable because Jorion, Liu, and Shi (2005) find that the market response to credit rating changes increased following Regulation FD (that came into effect on October 23, 2000), and a similar effect might be observed for credit watch announcements.

We estimate the regression model for down watches and up watches separately. Panel A in Table IX presents the results using all observations and Panel B presents the results using only noncontaminated observations. For up watches, regression results using all observations indicate that CAR is negatively and significantly related to *TotalAssets*, suggesting that the information content of up watches is smaller for larger issuers. Estimated coefficients on *InvestGrade* and *MultiNotch* are positive and significant at the 5% and 1% level, respectively, suggesting that the market response to up watches is stronger for investment grade issuers and in cases where the watch is followed by a multi-notch rating change. We find similar results when we estimate the model with noncontaminated observations only.

Regression results using the down watch sample indicate that the adverse effect of down watches on stock returns is smaller for investment grade issuers, and the result is robust to the exclusion of contaminated observations. Table IX also shows a positive and significant (at the 1% level) coefficient on *WatchDuration* for both the full sample and noncontaminated-only sample, indicating that the longer the watch duration, the smaller the adverse effect of down watches on stock returns.[52]

Finally, we find that estimated coefficients on *WtchDnRatUp* are negative and significant at the 1% level for down watches, irrespective of whether we use all observations or only noncontaminated observations in the regression. For up watches, the estimated coefficient on *WtchUpRatDn* is negative and significant at the 5% level when we use only noncontaminated

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announcements triggered by those discrete events, then removal of contaminated credit watch observations will reduce the overall magnitude of the price response to those credit watches.

[51] All variables are 98% winsorized. See Exhibit 2 for variable definitions and data sources.

[52] One might ask how the market anticipates the watch duration at the time of the watch action. One possibility is that market participants interpret the tone of watches when watches are issued. If a watch that will take longer to resolve is issued with a more uncertain tone, the market response will be weaker. This “weaker tone” story is consistent with the mean and median watch durations reported in Table II, Panel C, where the duration for nonconcordant down watches is relatively long. A longer watch duration might be a manifestation of a CRA’s uncertain position regarding the future watch resolution, and this weak position may be conveyed at the time of watch actions. For up watches, although the *WatchDuration* variable is not significant, the sign is still negative, suggesting a weaker positive market reaction. A similar story can be applied to the significantly positive *Multinotch* estimated coefficient. A watch that precedes a multi-notch rating change may be issued in a stronger tone, leading to a stronger market response.

Table IX. Cross-Sectional Analysis of Abnormal Returns Surrounding Watch Start Dates

This table presents results from estimation of a regression model where the three-day CAR surrounding the watch start date is the dependent variable. Abnormal returns are market model residuals using the CRSP value weighted index and an estimation period of days (−150, −46) relative to the watch start date. Independent variables include indicator variables representing different watch action/rating direction combinations (*WtchDnRatUp* and *WtchDnRatDn* for down watches, and *WtchUpRatUp* and *WtchUpRatDn* for up watches), *TotalAssets*, *postFD, InvestGrade*, *WatchDuration*, *Multinotch, ConcEvent*, *FinanPerf*, *M&A*, and year dummies. All variables are 98% winsorized. See Exhibit 2 for variable definitions and data sources. The regression model is estimated for down watches and up watches separately. Panel A presents results using all observations in estimation, and Panel B presents results using noncontaminated observations only. The *t*-statistic is used to test for a significant difference between the estimated coefficient and zero. *N* denotes the number of observations.

	Panel A. All Observations		Panel B. Noncontaminated Only	
Independent Variable	**Down Watches**	**Up Watches**	**Down Watches**	**Up Watches**
Intercept	−0.0002	0.0485**	−0.0103	0.0289
	(−0.01)	(2.17)	(−0.38)	(1.06)
WtchDnRatDn	−0.0144***		−0.0178***	
	(−3.32)		(−2.99)	
WtchDnRatUp	0.0034		0.0440	
	(0.17)		(1.44)	
WtchUpRatUp		−0.0018		−0.0009
		(−0.36)		(−0.16)
WtchUpRatDn		−0.0162		−0.1078*
		(−0.73)		(−2.26)
TotalAssets	−0.0027**	−0.0052***	−0.0015	−0.0045***
	(−2.27)	(−3.99)	(−0.950)	(−3.06)
postFD	0.0076	0.0298	−0.0008	0.0118
	(0.54)	(1.63)	(−0.04)	(0.48)
InvestGrade	0.0159***	0.0112***	0.0165***	0.0135**
	(3.77)	(2.27)	(3.01)	(2.36)
WatchDuration	0.0001***	0.0000	0.0001**	0.0000
	(2.81)	(−1.54)	(2.02)	(−1.52)
Multinotch	0.0001	0.0253***	−0.0050	0.0208***
	(0.01)	(5.26)	(−0.88)	(3.80)
DiscreteEvent	−0.0159***	0.0074	−0.0021	−0.0031
	(−3.69)	(1.21)	(−0.31)	(−0.37)
FinanPerf	−0.0063	−0.0076	0.0004	−0.0090*
	(−1.46)	(−1.46)	(0.07)	(−1.72)
M&A	0.0373***	0.0222***	0.0151	−0.0048
	(6.99)	(3.39)	(1.40)	(−0.49)
F-value	5.56	6.79	1.90	3.12
Adjusted R^2	0.063	0.145	0.024	0.099
N	1,900	960	1,025	541

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

observations. These results suggest that the market reaction to a credit watch is related to the eventual outcome of the watch.

B. Abnormal Returns Associated with Credit Watch Resolutions

In a final set of analyses, we examine the abnormal stock returns associated with rating actions. This work is motivated by issues examined in Holthausen and Leftwich (1986), Hand et al. (1992), and Goh and Ederington (1993). Holthausen and Leftwich (1986) expect to observe smaller absolute market responses to those rating changes that are in the same direction as the preceding watch. They analyze contaminated rating upgrades, contaminated downgrades, noncontaminated upgrades, and noncontaminated downgrades. Their expectation is supported for the contaminated rating downgrade subsample only. Holthausen and Leftwich (1986) state that in an unreported analysis, they find that mean abnormal returns associated with 222 watch resolutions (where the rating is revised in the indicated direction or affirmed) are not significantly different from zero. Hand et al. (1992) examine stock and bond returns associated with rating changes,[53] and perform cross-sectional analyses of excess bond returns. They find that the magnitude of excess bond returns is different from zero for rating changes that are preceded by credit watches.[54] Goh and Ederington (1993) show that rating downgrades have different value implications, depending on what triggered them.

Our investigation begins with a descriptive analysis of CARs associated with rating changes partitioned by watch type. We find significantly negative CARs in the down rating/down watch and down rating/no prior watch partitions (two-sided tests, 1% level), regardless of whether we include/exclude contaminated observations.[55] This result suggests that credit watch actions do not preempt the information conveyed by rating downgrades. Consistent with both the finding of Holthausen and Leftwich (1986) and the prediction of Boot et al. (2006) we find that CARs associated with rating upgrades are not significantly different from zero, regardless of the watch action and with or without contaminated observations. In contrast to the prediction of Boot et al. (2006) however, we do not find that rating changes that are preceded by a down watch are more informative than those that are not preceded by a down watch. These results are suggestive only, since we do not control for other potentially relevant variables that may affect the market response to rating changes.[56]

[53] Hand et al. (1992) analyses of abnormal stock and bond returns associated with rating change announcements do not use expected and unexpected subsamples of rating changes, since use of an expectations model did not strengthen results as in the case of watch actions. Their stock return results are similar to those reported in H&L: Negative abnormal returns are associated with rating downgrades, and abnormal stock returns associated with rating upgrades are not significantly different from zero. Abnormal bond returns associated with rating upgrades are significantly positive. Abnormal bond returns associated with rating downgrades are significantly negative for the entire sample, and not significantly different from zero for the noncontaminated subsample. See Kose, Ravid, and Reisel (2010) and Livingston and Zhou (2010) for recent evidence regarding the information content of debt ratings.

[54] Hand et al. (1992) conducted separate regression analyses for contaminated and noncontaminated subsamples of rating upgrades only and rating downgrades only.

[55] The mean winsorized CARs are as follows: 1) All observations: rating down/watch down mean CAR is −0.013 (1,217 observations), rating down/ no prior watch CAR is −0.02 (2,092 observations); 2) Noncontaminated only observations: rating down/watch down mean CAR is −0.011 (862 observations), rating down/no prior watch CAR is −0.013 (1,495 observations).

[56] We estimate multiple regression models to obtain further evidence of the information-conveying role of credit watches. In these models, the three-day CAR surrounding the rating change date is the dependent variable, and independent variables include indicator variables representing different watch action/rating direction combinations (*WtchDnRatDn*, *WtchUpRatDn*, and *WtchUncertainRatDn* for the rating downgrades analysis, and *WtchDnRatUp*, *WtchUpRatUp*, and *WtchUncertaiRatUp* for the rating upgrades analysis), *TotalAssets*, *postFD*, *InvestGrade*, *WatchDuration*, and *Multinotch*.

C. Additional Tests of Boot et al. (2006) Predictions

Boot et al. (2006) predict that return volatility at credit rating change announcements will be relatively greater for changes preceded by negative watches. We test this prediction by comparing the mean return volatility for rating changes preceded by down watches with the mean volatility associated with rating changes not preceded by watches. We follow the approach of Bhattacharya, Douk, Jorgenson, and Kehr (2000, pp. 78–79), where volatility for each rating change is calculated as the three-day (-1, 0 and $+1$) sum of |rank of daily abnormal returns—45.5|. The daily abnormal return rank is determined by using days -80 to $+10$ (a total of 91 days), yielding a median rank of 45.5. Our results show that the mean volatility of the rating change announcements preceded by negative watches is 13.20, which is not greater than the mean volatility of 15.23 observed for the no-watch group. These results are not consistent with the Boot et al. (2006) prediction.

Boot et al. (2006) also predict that if the price impact at the watch initiation is small, there will be a more negative market response to a subsequent downgrade because the market initially anticipates only a small likelihood of a downgrade. We test this prediction as follows. First, we sort the down watch observations into three groups according to their three-day CARs: "large price drop," "middle price drop," and "small price drop." We then calculate the mean three-day CAR (full sample) and the mean three-day CAR (noncontaminated sample) surrounding the rate change date for each of the three credit watch subsamples. We find that for both the full sample and the noncontaminated sample, the mean CAR for the "small price drop" credit watch group is less negative than the mean CAR for the "large price crop" credit watch group. This evidence is not consistent with the Boot et al. (2006) prediction.[57]

We find that the three-day CARs surrounding the rating confirmation date for the Baa and non-Baa rating subsamples (following down watches) are 0.004 (*t*-stat. 0.96) and 0.012 (*t*-stat. 3.57), respectively. These results are consistent with the prediction of Boot et al. (2006) that stock prices react *positively* to rating confirmations.

VIII. Summary and Concluding Remarks

This study provides empirical evidence that improves our understanding of the role of credit watches in the credit rating process. We begin by presenting descriptive evidence on the triggering events and underlying causes that lead to watch actions, using Moody's press releases made at the time of watch actions. We show that watch actions are more frequently prompted by specific, publicly known events such as mergers or acquisitions than are rating actions, indicating substantive differences between watch and rating actions in terms of triggering events. We also

(See Exhibit 2 for variable definitions.) We include the dummy variables representing different watch action/rating direction combinations in the regression model to test whether the market reaction around the rating change date varies with the type and presence of a preceding credit watch. We estimate the regression models for rating downgrades and upgrades separately. For rating downgrades (regardless of whether we include/exclude contaminated observations), we find that the three-day CAR is positively and significantly related to *InvestGrade*, indicating that rating downgrades have a smaller negative impact on stock returns for high credit quality issuers; and that multi-notch rating downgrades have a greater negative market impact than one-notch rating downgrades. For the all-observations subsample only, we also find that the regression coefficient on *WtchUpRatDn* is negative and significant, indicating that rating downgrades have a greater negative impact on abnormal returns when they are preceded by a credit watch in the opposite direction. Our results indicate that issuer size, Regulation FD, and watch duration have no effect on the abnormal returns. We find no significant results in the regressions for rating upgrades.

[57] Analysis using the volatility measure of market response shows that the mean volatility surrounding rating changes in the "large price drop" credit watch subsample is about 3.6 times as large as the mean volatility associated with the "small price drop" credit watch subsample.

examine factors associated with the likelihood that a rating change is preceded by a credit watch. Our evidence is generally consistent with the expectation that the likelihood that a rating change is preceded by a watch action varies systematically with proxies for investor demand for credit quality information and the adverse consequences of issuing a rating change prematurely.

We show that credit watches occur more often in response to deterioration in credit quality and that issuers attempt to address the concerns that prompt Moody's down watches. These results support the view of Boot et al. (2006) that the credit watch may be viewed as an implicit contract between the issuer and the CRA where the issuer agrees to act to prevent the lowering of its credit rating. Consistent with the implication of the Boot et al. (2006) model, we also find evidence that down watches are less likely than up watches to indicate the direction of the subsequent rating change.

We find that down and up watches are associated with statistically significant negative and positive abnormal stock returns, respectively. Hence, our results do not support the view of Boot et al. (2006) that credit watches are noninformational events because all market participants can observe the change in credit quality. In general, our results support the hypothesis that credit watches enhance CRAs' information-supplying role and facilitate the use of credit ratings in contracting.

Exhibit 1. Triggering Events and Underlying Causes for Credit Watch Actions

This exhibit describes the categories used to classify triggering events that lead to credit watches and stated reasons for issuing the credit watch, as discussed in Moody's press releases announcing the watch actions. The same categories are used for classifying rating actions.

Triggering Events that Lead to Credit Watches[58]	
Discrete Event	The issuer has announced plans or events expected to affect credit quality, but which are not certain to take place and/or whose effect on credit quality is uncertain. Examples include acquisitions, mergers, restructuring (including asset sales), and becoming a target. This category also includes the occurrence of a sudden event that changes the issuer's operating environment, but the magnitude of its effect on the issuer is not clear. This second type of discrete event is uncommon in our sample.
Issuer or Environmental Trend	Trends are observed in the issuer's operations or financial strength, in its industry or regulatory environment, or in the macroeconomic climate of its country or region of operation that might affect the issuer's credit quality.

Underlying Causes for Credit Watch Actions	
Financial Performance	Trends, results, or events related to earnings, operating income, sales, cash flow, interest coverage, and/or costs.
Leverage and Balance Sheet Related	Trends, results or events related to leverage, related measures, and/or to creditor protection, and other balance sheet measures and ratios. The latter category includes references to the issuer's credit profile, limited financial flexibility, balance sheet strength, etc.

[58] See Keenan, Fons, and Carty (1998).

Acquisition	Issuer plans or agrees to acquire an entity.
Target	Issuer plans or agrees to be acquired by an entity.
Merger	Issuer plans or agrees to merge with another entity.
Restructuring	Financial outcomes related to restructuring, consolidation of facilities to improve operating results, and/or recognition of significant charges related to reductions to cost structure.
Other Reasons	Economic trends or conditions, industry trends or conditions, delays or expected delays in filing financial statements, regulatory uncertainties, legal issues, technical default under loan agreements, bankruptcy, accounting restatements, lack of transparency by management, and other items.

Exhibit 2. Variable Descriptions

(Data Source is Moody's Default Risk Service (DRS) Database, Except as Noted.)

Dependent Variables Used in Regression Estimations	
DnRateWthWatch	Indicator variable that equals one if downgrade is preceded by a credit watch, and zero if downgrade is not preceded by a watch. The variable is used in Table V analyses involving samples containing rating downgrades only.
UpRateWthWatch	Indicator variable that equals one if upgrade is preceded by a credit watch, and zero if upgrade is not preceded by a watch. The variable is used in Table V analyses involving samples containing rating upgrades only.
BothRateWithWatch	Indicator variable that equals one if a rating upgrade or downgrade is preceded by a credit watch, and zero if the rating change is not preceded by a watch. The variable is used in Table V analyses involving samples containing both rating upgrades and downgrades.
WatchRateConcord	Indicator variable that equals one for down watches followed by rating downgrades and up watches followed by rating upgrades. The variable equals zero for down watches followed by rating confirmations or upgrades, and for up watches followed by rating confirmations or downgrades. The variable is used in Table VI analyses. These analyses use samples containing rating upgrades, downgrades, and confirmations combined.
CAR	Three-day buy-and-hold abnormal return cumulated over trading days (−1,1) surrounding day 0 (either the watch action date or the letter rating change date, depending on the analysis). Abnormal returns are market model residuals estimated over days (−150, −46), where CRSP value-weighted returns are used for the market return. *Source: CRSP*.

Independent Variables Used in Regression Estimation	
AbsROA	Absolute value of *ROA*, where *ROA* is defined as net income before extraordinary items divided by beginning-of-year total assets. *Source: Compustat.*
DiscreteEvent	Indicator variable that equals one for a credit watch triggered by a discrete event (see Exhibit 1), and zero otherwise. *Source: Analysis of Moody's press releases.*

CostDebt	Interest expense divided by the sum of short-term and long-term debt. *Source: Compustat.*
A, Baa, Ba, Caa	Indicator variables for the broad credit rating in effect immediately preceding a rating or watch action. *A* equals 1 for rating category A, and 0 otherwise; *Baa* equals 1 for rating category Baa, and 0 otherwise; *Ba* equals 1 for rating category Ba, and 0 otherwise; and Caa equals 1 for rating categories *Caa*, Ca, and C, and 0 otherwise.
FallAngel	Indicator variable that equals one for fallen angels (issuers downgraded from investment to noninvestment grade) and zero otherwise
FinanPerf	Indicator variable that equals one for a credit watch having a financial performance-related underlying cause (see Exhibit 1), and zero otherwise. *Source: Analysis of Moody's press releases.*
FromDefault	Indicator variable that equals one for rating upgrades from default grade to non-default grade, and zero otherwise.
InvestGrade	Indicator variable that equals one if credit rating is investment grade prior to watch action, and zero otherwise.
M&A	Indicator variable that equals one for a credit watch having a merger, acquisition, or target-related underlying cause (see Exhibit 1), and zero otherwise. *Source: Analysis of Moody's press releases.*
MultiNotch	Indicator variable that equals one for rating changes greater than one notch, and zero otherwise. A notch is the difference between adjacent ratings (where a rating consists of the generic rating category (e.g., Aa) including numerical modifiers (1, 2, and 3). For example, a downgrade from Aa2 to Aa3 is a single notch rating change. A downgrade from Aa1 to Aa3 is a multi-notch rating change.
PostFD	Indicator variable that equals one if the watch date is after October 23, 2000, and zero otherwise.
RateDays	Number of calendar days between the current rating change date and the prior rating change date.
RateDown	Indicator variable that equals one for rating downgrade, and zero otherwise.
RegIndustry	Indicator variable that equals one for firms in the public utility and finance industries, and zero otherwise. *Source: Compustat.*
RiseStar	Indicator variable that equals one for 'rising stars' (issuers upgraded from noninvestment to investment grade), and zero otherwise.
ToDefault	Indicator variable that equals one for rating downgrade to default grade (*Caa*, Ca, and C rating categories), and zero otherwise.
TotalAssets	Natural logarithm of issuer's total assets (millions $US). In Tables V and VI, *TotalAssets* is as of the most recent fiscal year-end preceding the rating change. *Source: Compustat*
Watch Down	Indicator variable that equals one for a down watch, and zero otherwise.
WatchDuration	Number of calendar days between watch start and end dates.
WtchDnRatUp	Indicator variable that equals one for a down watch followed by a rating upgrade, and zero otherwise.
WtchDnRatDn	Indicator variable that equals one for a down watch followed by rating downgrade, and zero otherwise.
WtchUncertRatDn	Indicator variable that equals one for an uncertain watch followed by a rating downgrade, and zero otherwise.
WtchUpRatUp	Indicator variable that equals one for an up watch followed by a rating upgrade, and zero otherwise.
WtchUpRatDn	Indicator variable that equals one for an up watch followed by a rating downgrade, and zero otherwise.

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