Do Credit Rating Agencies Sacrifice Timeliness by Pursuing Rating Stability? Evidence from Equity Market Reactions to *CreditWatch* Events

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Abstract

Credit rating agencies argue that markets expect them to issue stable ratings. Examining equity market reactions around *CreditWatch* events in 2002-2005, we find evidence that the pursuit of stable rating policies may reduce the timeliness of rating changes. Abnormal equity returns of a firm *prior* to being listed on *CreditWatch* are effective predictors of the ultimate change in rating that occurs when the firm is delisted. Equity markets exhibit no reaction when a firm is delisted from *CreditWatch*, suggesting information about the rating change is already reflected in equity prices at the time of delisting.

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Do Credit Rating Agencies Sacrifice Timeliness by Pursuing Rating Stability? Evidence from Equity Market Reactions to *CreditWatch* Events

One of the most surprising events during the 2007-2008 financial crisis was the filing of Chapter 11 bankruptcy by Lehman Brothers, an investment bank with a 158-year history, on Monday, September 15th, 2008. The news of Lehman's collapse shook financial markets world-wide, including a drop in the Dow Jones Industrial Average of more than 500 points. The collapse of Lehman took many investors by surprise because as recently as September 12th, the previous Friday, Lehman Brothers' bonds were rated "A", an investment grade.

Though unique in its impact on global markets, the precipitous fall of Lehman from investment grade status directly to bankruptcy is not unprecedented. Several other high-profile bankrupt companies, including Enron, also maintained investment-grade ratings until just days before the bankruptcy was announced. Are rating agencies too slow in adjusting ratings?

Indeed, one major criticism of credit rating agencies is the lack of timeliness in making rating changes.¹ Studies in the finance literature have shown that credit rating changes are anticipated by the equity market (Norden and Weber (2004)), the credit default swaps market (Hull, Predescu, and White (2004); Norden and Weber (2004)), the currency market and the sovereign debt market (Reinhart (2002); Sy (2004)). Thus, credit rating agencies have faced such criticism long before the 2007-2008 financial crisis.

The difficulty of rating agencies to convey timely default information to the market is a

¹ For instance, in response to the failure of Enron in December 2001, the Senate criticized credit rating agencies for not downgrading the company's debt rating soon enough. The Staff Report of the US Senate Committee on Governmental Affairs indicated that the credit agencies' monitoring and review of Enron's finances "fell below the careful efforts one would have expected from organizations whose ratings hold so much importance".

deep-rooted problem for several reasons. First, rating agencies may not have timely or accurate information on debt issuers' financial positions (Goldstein, Kaminsky, and Reinhart (2000)), or they may not use the best rating methodologies or expend maximum effort (Cheng and Neamtiu (2009)). Second, while the financial positions of rated companies are constantly changing, the change in credit ratings can only be made periodically. As a result, a lag of credit ratings in reflecting the changes in financial positions may be inevitable. Third, default probability is a continuous variable, but credit ratings, which are indications of default likelihood, are discrete. A rating agency cannot make a rating change until the financial position of a company deteriorates to the next rating level. As a result, rating changes may lag the change in bond issuer's default probability.²

Another reason for the slow reaction may be related to an argument put forth by rating agencies that markets expect *stable* ratings. Ratings are often used by investors and regulators as guidance for portfolio governance.³ Frequent changes in ratings may force portfolio managers to trade securities more frequently, thereby increasing transaction costs. Frequent rating changes may also force portfolio managers to sell securities at lower prices (when they are downgraded) and to purchase at higher prices (when they are upgraded) more frequently, rating agencies tend to meet the

² Both Moody's Investors Service and Standard & Poor's have adopted refined rating categories by adding modifiers (e.g. "+" and "-", or "1", "2", and "3") to the generic rating categories to indicate whether a bond is on the upper, middle, or lower end of the rating category. The refinement of the rating categories can be viewed as a step moving from a discrete rating system toward a continuous spectrum. So refined ratings not only reflect the default probability more precisely, they also may trigger a rating change more quickly as rating agencies do not have to wait until the financial positions of bond issuers to deteriorate (or improve) to the next broader generic rating category to make rating changes.

³ For instance, financial institutions such as banks and pension funds are often required to hold "investment grade" bonds only in order to show their "prudence" in fund management. As a result, when a bond is downgraded to "speculative grade", they must sell the bond at a loss.

market expectations by making rating changes only when a *reversal* in ratings in the near future is unlikely (Cantor (2001); Cantor and Mann (2007)). Studies in the literature also show that the policy of issuing stable ratings allows rating agencies to focus on bond issuers' permanent, long-term and structural credit risk, rather than the short-term and temporary credit risk (Altman and Rijken (2004)).⁴

Loffler (2005), however, argues such a policy of stable ratings may lead to a lag of rating changes behind the true changes in bond issuer's default risk. While investors may have some expectation of rating stability, they also expect rating agencies to make changes in a timely fashion. If rating agencies sacrifice timeliness for the sake of stability, markets may work faster than the rating agency and price in much of information about the changing default risk of the firm before a rating change occurs. Undoubtedly, investors would benefit from timely rating changes, especially during financial crises when investors are urgently seeking new information about the default risk of a firm.

Credit rating agencies have not been insensitive to the criticism. One specific action by Standard and Poor's (S&P's) was the creation in of a service known as *CreditWatch*, which was first offered in November 1981. *CreditWatch* provides information to investors about potential changes in default risk prior to an actual change in rating. One major purpose of *CreditWatch* is to ease the tension between the market expectation of rating stability and the market demand for rating timeliness (Altman and Rijken (2006)).

When a company is listed on CreditWatch, it is typically listed with either a positive or

⁴ Standard & Poor's (2003) indicates that the value of its rating products is greatest "when its ratings focus on the long-term and do not fluctuate with short-term performance." Similarly, Moody's Investors Service makes rating changes "only when it believes an issuer has experienced what is likely to be an enduring change in fundamental credit worthiness" (Cantor and Mann, October 2003).

a *negative* potential.⁵ In a listing with positive potential, the rating of the company will usually be eventually upgraded or affirmed (i.e. unchanged), and the rating is rarely downgraded. Similarly, in a listing with negative potential, the rating of the company will usually be eventually downgraded or affirmed, and the rating is rarely upgraded. Once the rating is changed or affirmed, the listed company is delisted (removed) from the *CreditWatch* list. Unlike credit rating changes in which rating agencies convey the default risk to the market in one action (i.e. the rating change), the publication of *CreditWatch* conveys the default information to the market through two sequential actions – first through *listing*, and then through *delisting*. The listing conveys information about the direction of the rating change, and the delisting reveals the magnitude of the actual rating change. Although listing on *CreditWatch* can lead to a bond rating change, only a small fraction of all actual rating changes are preceded by a listing on *CreditWatch*.

In this study, we examine the response of equity prices of firms listed and delisted from *CreditWatch* to determine if it improves the timeliness of rating changes. We choose to examine the reaction of equity markets (instead of debt markets) because equity investors have the most to lose from default, so prices in equity markets are more sensitive to changes in default risk. Equity markets are also considerably more liquid than bond markets and the data for equity prices are readily available. Moreover, Wansley and Clauretie (1985) examine the reaction of both equity and bond markets to *CreditWatch* events, and conclude that bond markets are considerably less efficient than equity markets.

⁵ Infrequently, Standard & Poor's will place a company on the *CreditWatch* list under a third category known as "developing." When a company is listed as "developing", it means the credit rating of the company is likely to be changed, but the *direction* of the change is unknown. The number of companies listed as "developing" is far less than the number of companies listed with *positive* or *negative* potentials. We do not include bonds listed as "developing" in our study.

Despite its intended purpose of informing investors of a potential rating change in a timely fashion, we find that *CreditWatch* does not completely achieve this goal. We report three empirical results in support of this conclusion. First, we find equity markets experience substantial positive (negative) reaction to the listing of companies with positive (negative) potential on *CreditWatch prior* to the actual date of listing. Second, equity markets exhibit little reaction to the delisting of a company from *CreditWatch*, even when the delisting is accompanied by a change in rating. Third, we find that the pre-listing abnormal returns in equity markets are good predictors of both the direction and the magnitude of the eventual change in credit rating. Collectively, our findings suggest that rating agencies may sacrifice timeliness for the sake of stability and that even *CreditWatch*, which is designed to mitigate the disadvantage caused by stable rating policies, is not a completely effective instrument.

The remainder of the paper is organized as follows. Section I discusses the data and the methodology. Section II presents the empirical analyses and results, and Section III concludes.

I. Data and Methodology

A. Sample Construction and Description

Our sample construction begins with firms placed on *CreditWatch* between January 2002 and December 2005. We hand-collect the following data: 1) company name, 2) listing date, 3) existing S&P senior debt rating, 4) listing potential, and 5) new S&P senior debt rating after delisting. From this group, we exclude all firms with insufficient data from the Center in Research and Security Prices (CRSP) to compute abnormal returns surrounding the listing date. We also exclude firms for which definitive information about the action taken by S&P regarding the firms' rating upon delisting is unavailable. The final sample consists of

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604 observations, with 101 listed with "positive" potential, 503 listed with "negative" potential.⁶ The sample composition is consistent with similar studies in the literature (e.g. Dichev and Piotroski (2001); Hand, Holthausen, and Leftwich (1992); Holthausen, and Leftwich (1986)) in that downgrades are considerably more common than upgrades.

Following Morgan (2002), we transform letter ratings into a numerical scale with higher quality ratings transformed into lower numbers. The details of the transformation are provided in Appendix I. Tables I and II report the frequency distributions of the initial rating and the new rating upon delisting for companies listed with "positive" and "negative" potentials, respectively. For listings with positive potential, approximately 80% of firms are upgraded when delisted from *CreditWatch*. For firms listed with negative potential, approximately 60% are downgraded when delisted.

Insert Tables I and II here.

Table III reports basic financial characteristics of the firms in the sample categorized by type of listing. Financial data is obtained from Compustat for the year preceding the date of listing. The sample sizes are reduced slightly because of missing data in Compustat. Statistically significant differences exist regarding the size of the companies (measured by total assets) and the cash ratio. Specifically, firms listed with negative potential are larger in size and have lower cash ratios compared to firms listed with positive potential. Firms listed with positive potential tend to remain on the *CreditWatch* list longer than those listed with negative potential, but the difference is not statistically significant. A breakdown of the number of firms by the first digit of the Compustat SIC code is provided in Appendix II.

⁶ There is one (five) extremely rare cases in which firms were listed with positive (negative) potentials but were downgraded (upgraded). We report these observations in our descriptive statistics, but exclude them from further analysis.

Insert Table III here.

B. Methodology

To capture the reaction of the equity market, we employ an event study methodology by computing daily abnormal returns (AR) and cumulative abnormal returns (CAR) of the companies in event windows surrounding the listing and delisting dates. For robustness, we consider three estimation procedures – the market model, market adjusted return model, and the Fama-French (1992) model – to calculate the abnormal returns. The market index is the CRSP value-weighted index and the daily Fama-French factors are also obtained from CRSP. The estimation period is the 200 trading days ending 61 trading days prior to the event date.

The market model is specified as a single factor model with the rate of return of a common stock as a function of the return of a market index:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \tag{1}$$

Where R_{jt} is the rate of return of the common stock of firm j on day t; R_{mt} is the rate of return of a market index on day t; ε_{jt} is the error term -- a random variable that, by construction, must have an expected value of zero, and is assumed to be uncorrelated with R_{mt} . The coefficient β_i is a parameter that measures the sensitivity of R_{jt} to the market index.

Market model abnormal return (or prediction error) for the common stock of the firm j on day t, AR_{jt} is defined as:

$$AR_{jt} = R_{jt} - (\hat{\alpha}_{j} + \hat{\beta}_{j}R_{mt})$$
⁽²⁾

where the coefficients $\hat{\alpha}_{j}$ and $\hat{\beta}_{j}$ are ordinary least squares estimates of α_{j} and β_{j} .

The market adjusted return model computes abnormal returns by simply subtracting the

observed return on the market index from the rate of return of the common stock:

$$AR_{jt} = R_{jt} - R_{mt} \tag{3}$$

The Fama-French (1992) three-factor model states that security prices are determined by three factors, defined as:

$$ER_{jt} = \alpha_j + \beta_j ER_{mt} + S_j SMB_t + h_j HML_t + \varepsilon_{jt}.$$
(4)

where ER_{jt} is the excess rate of return of the common stock beyond the risk-free rate of firm j on day t; ER_{mt} is the excess return of the market index beyond the risk-free rate on day t; SMB_t is the average return on small market-capitalization portfolios minus the average return on three large market-capitalization portfolios; HML_t is the average return on two high bookto-market equity portfolios minus the average return on two low book-to-market equity portfolios; ε_{jt} is the error term. The abnormal return (or prediction error) for the common stock of firm j on day t is computed as:

$$AR_{jt} = ER_{jt} - (\hat{\alpha}_{j} + \hat{\beta}_{j}ER_{mt} + \hat{S}_{j}SMB_{t} + \hat{h}_{j}HML_{t})$$
(5)

Cumulative abnormal returns are the sum of daily abnormal returns over a specified time period. For all three models, the CAR from trading day T_1 through T_2 is computed for firm j as:

$$CAR_{j,(T_1T_2)} = \sum_{t=T_1}^{T_2} AR_{jt} .$$
(6)

where T_1 and T_2 are the beginning and ending days of the event window, respectively.

II. Empirical Results

Our goal in this paper is evaluating the ability of *CreditWatch* to convey information to markets in a timely fashion. Accordingly, we examine the equity market's reaction to both the listing on and delisting from *CreditWatch*. We also examine to what extent the rating action that occurs upon delisting (i.e. an affirmed rating or a change in rating) is reflected in the abnormal returns.

A. Equity Market Reaction to CreditWatch Listing

To assess whether *CreditWatch* listings reflect the changes of the listed companies' financial positions in a timely fashion, we calculate the daily AR on days surrounding the date of listing and the CAR for several event windows. For robustness, we use three different return generating models, as described in the previous section. Separate results of the mean values for listings with positive and negative potential are presented in Table IV.

Insert Table IV here.

Analysis of the daily AR shows a significant positive (negative) reaction by the market on the day of a listing (Day 0) with positive (negative) potential. Taken alone, this finding suggests that a listing on *CreditWatch* provides the market with new information. However, the magnitude of the reaction on the day of listing is often substantially smaller than the CAR present in the days prior to the listing date, suggesting the listing on *CreditWatch* is somewhat delayed. This trend is particularly pronounced for those firms listed with negative potential. For example, the market adjusted model abnormal return on Day 0 is -2.84%, but CAR_(-30,-1) is nearly three times as large at -8.20%.

Although the abnormal returns are both statistically and economically significant on the listing day, we cannot conclude whether the return on the listing day was due to the

announcement of the *CreditWatch* list, or it is part of the continuing adjustment process that may have started as early as 60 days before the listing. Even if the significant abnormal return on the listing day is entirely related to the announcement of the listing, the results still indicate the placement of firms on *CreditWatch* may not be timely enough. Regardless of the specification for computing abnormal returns (the market model, market adjusted return model, or the Fama-French model), the results in Table IV suggest that equity markets have reflected a substantial portion of the change in listed firms' financial positions *before* the listing day. For robustness, we also examine the median values of the daily AR and CAR, and the results (unreported) confirm the findings of the analysis using the value of the means.

We next examine the equity market reaction surrounding the listing date categorized by the delisting action. We classify the listed companies into four categories based on the magnitude of the actual change in rating that occurs on the delisting day. The four categories are: no rating change (i.e. rating being affirmed), a small rating change (changed by one notch), a medium rating change (changed by two notches), and a large rating change (changed by three notches or more). The subcategories are further separated for companies listed with positive and negative potential, creating a total of eight possible categories. The mean daily AR and CAR over various event windows surrounding the listing date for each category are presented in Table V. To conserve space, we report only the results from the market model estimation throughout the remainder of the paper, but both the market adjusted return model and the Fama-French models produces results qualitatively similar to those from the market model.

Insert Table V here.

The results in Table V provide considerable evidence suggesting a positive correlation

between the magnitude of the CARs prior to the listing day and the magnitude of the rating changes announced on the delisting day. For positively listed companies, the magnitude of the CARs prior to the listing day does not monotonically increase with the magnitude of rating changes, but we find the average magnitude of the CARs for companies within the two smallest rating change categories (i.e. companies whose ratings were affirmed or were changed by one notch) are smaller than the CARs for companies with two larger rating change categories (i.e. companies were changed by two notches or three notches or more).

For companies listed with negative potentials (which is a much larger sample compared to the listings with positive potential), the evidence is much stronger. The magnitude of the CAR prior to the listing, regardless of the event window, exhibits a consistent monotonic trend. This is strong evidence that equity markets have anticipated *prior* to the listing date not only the *CreditWatch* listing potential (positive or negative), but also the change in rating at delisting. This point is well-illustrated in Figure 1, which plots CAR_(-7,+3) for the eight categories. Despite some notable reaction on the day of announcement, the adjustment process in equity prices begins well before then, particularly for listings that ultimately result in rating changes of at least two notches. The results suggest that *CreditWatch* is still not timely enough in conveying the information about the change of financial positions of listed firms to the market.

Insert Figure 1 here.

B. Equity Market Reaction to CreditWatch Delisting

Having provided evidence that the magnitude of the rating change at delisting is reflected in equity prices *prior* to the listing announcement, we next examine the information content of the delisting event by computing the AR and CAR surrounding the date of delisting.

Insert Table VI here.

Table VI presents the daily AR and CAR over various event windows surrounding the delisting date by the type of action that occurs when the company is delisted from *CreditWatch*. We take care to ensure that none of the pre-delisting windows overlap with post-listing windows. The results in Table VI are noticeably different from those presented in Table V for the listing date, as there is very little market reaction on the day of the delisting announcement (Day 0). This is true regardless of whether the firm was listed with positive or negative potential, and also irrespective of the magnitude of the rating change upon delisting. The results suggest that the announcement of delisting (in which the actual rating changes are made) contains limited information.

C. Predicting the Change in Rating

We have shown equity markets experience significant reactions in the days *prior* to a firm's listing day. We have also shown markets exhibit little reaction on the day a firm is delisted from *CreditWatch*. We now examine whether the pre-listing equity market reaction is an effective predictor of the eventual change in rating upon delisting. If it is, then *CreditWatch* is too slow in reflecting the changes in the firms' financial positions.

While the results in Table V and Figure 1 suggest that pre-listing CARs may serve as good predictors of rating changes, we now provide additional statistical support. To ascertain

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the degree of statistical significance, we regress the magnitude of the rating change at delisting on the CARs from the listing period using OLS estimation. Recall that higher rated bonds receive lower numerical scores, so an upgrade (downgrade) results in a negative (positive) value for the dependent variable. The results for several specifications of this model are presented in Table VII.

Insert Table VII here.

Model 1 contains only the CARs from the listing period as independent variables.⁷ The CARs for both the pre-listing (LIST_CAR (-7,-1)) and listing date (LIST_CAR(0,0)) are negative and statistically significant, and an F-test for the equality of coefficients shows that the magnitude of the listing date CAR is significantly greater. This suggests that the announcement day contains significantly more information than the pre-listing period. However, the inclusion of additional control variables eliminates this statistical difference.

Model 2 adds control variables for the time between the listing and delisting dates (SPAN) and the initial numerical rating at the time of listing (LIST_RATING). We also include dummy variables to control for proximity to the threshold between investment-grade and speculative-grade (junk) status. A bond rating of BB+ and below is considered junk status. Prior research (e.g. Brister, Kennedy, and Liu (1994); Jorion and Zhang (2007)) has demonstrated movement into or out of junk status has a more pronounced impact on markets since many institutional investors are prohibited from holding junk bonds. NEAR_JUNK takes a value of one for *negatively* listed firms with an initial rating of BBB+, BBB, or BBB-. NEAR_JUNK bonds are most likely to be downgraded into the junk bond categories upon

⁷ We also consider the CARs surrounding the delisting date as independent variables in our regression models. These variables never achieved statistical significance and appear to have no relationship with the magnitude of the rating change, so we do not report them.

delisting. Similarly, NEAR_INVESTMENT takes a value of one for *positively* listed firms with an initial rating of BB+, BB, or BB-. NEAR_INVESTMENT bonds are most likely to be upgraded into investment-grade categories upon delisting. The addition of these two dummy variables reduce the magnitude of LIST_CAR(0,0), but both LIST_CAR(-7,-1) and LIST_CAR(0,0) retain statistical significance. Model 3 includes an interaction of the dummy variables NEAR_JUNK and NEAR_INVESTMENT with LIST_CAR(-7,-1). The interaction of LIST_CAR(-7,-1) with NEAR_JUNK is positive and significant.

Model 4 adds basic financial characteristics of the listed firms as control variables. We include the natural log of assets, LN(ASSETS), as measure of size, ROA as a measure of profitability, DEBT_RATIO as a measure of leverage, and CASH_RATIO as a measure of liquidity, but none of the variables have a statistically significant impact on the magnitude of the rating change.

As a robustness check, Models 5 and 6 repeat the variable structure of Model 4, but separate the observations into categories of positive and negative potentials, respectively. Separating the sample into these two categories results in a truncation of the dependent variable (i.e. the change in rating), so we estimate Models 5 and 6 using a Tobit procedure. The results for both Models 5 and 6 are consistent with the findings in Models 1 through 4. The pre-listing and listing day CARs are statistically related to the change in rating upon delisting.

To ascertain the economic significance of our results, consider the coefficient for LIST_CAR(-7,-1) in Model 4 of -1.515. A one percentage point decline in the pre-listing CAR is associated with a rating downgrade of about 0.015 notches. At first glance this may seem trivial, but the mean pre-listing CARs from Table V are substantially larger than 1%.

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The fact that the pre-listing CARs are good predictors of rating changes upon delisting suggest that the *CreditWatch* is still too slow in reflecting the changes in firms' financial positions.

D. Robustness Checks

Probit Model

As a robustness check, we perform ordered probit regressions using the same variable structures as Models 1, 2 and 4 in Table VII. The results are presented in Table VIII, and confirm our previous findings. Separate intercepts are reported for each magnitude of rating change. The intercept values exhibit a monotonically increasing pattern. Both LIST_CAR(-7,-1) and LIST_CAR(0,0) are again statistically significant, but of a lower magnitude relative to Table VII. This finding is not surprising given that the ordered probit procedure provides a specific intercept for each category of rating change, instead of a single intercept as in the OLS and Tobit procedures in Table VII. The usefulness of pre-listing CARs in predicting the rating changes on the delisting date once again suggests that *CreditWatch* does not reflect the changes in the listed firms' financial positions timely enough.

Insert Table VIII here.

Initial Bond Quality

Studies in the literature (e.g. Brister, Kennedy, and Liu, 1994; Jorion and Zhang, 2007) have shown that for the same magnitude of downgrade (e.g. downgrade by one notch), the impact on a low-grade bond (e.g. from B+ to B) tends to be greater than a high-grade bond (e.g. from A+ to A) because low-grade bonds are closer to bankruptcy and they are more scrutinized by investors and regulators. As a robustness check of our results, we examine

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whether the same principles holds true for the CAR surrounding the listing on *CreditWatch*. We choose the largest category with similar rating changes, the one notch downgrades, and construct three sub-categories based on the initial rating: high ratings (A+), medium ratings (BBB), and low ratings (B+).

Insert Table IX here.

The results of the analysis are presented in Table IX, and demonstrate that the initial level of the rating is an important determinant of the magnitude of the CAR surrounding the *CreditWatch* listing date. The magnitude of CARs during the pre-listing period increases monotonically as the credit level decreases. For instance, the CARs over the period (-60, -1) are -2.19%, -8.97%, and -19.52% respectively for high rated (from A+ to A), medium rated (from BBB to BBB-), and low rated (from B+ to B) bonds. The pattern persists for the other pre-listing event windows as well, supporting the conclusions of prior research that for a given magnitude of rating change, the impact of rating changes is greater for lower rated bonds. The key difference, however, is that our results demonstrate equity markets are reasonably good at *predicting* the future rating change before the firm is placed on *CreditWatch*, especially for those firms listed with negative potential. The results once again suggest that *CreditWatch* does not reflect the change in the financial positions of listed firms' timely enough.

III. Conclusion

We examine whether rating agencies are sacrificing timeliness by pursuing rating stability by investigating the response of the equity market to the listing and delisting of firms on S&P's *CreditWatch*, a service whose intended purpose is to improve the timeliness of

information about changes in credit ratings. Despite its intended purpose, we find that *CreditWatch* is not completely effective at achieving this goal.

We report three empirical results that support our conclusion. First, we find that equity markets experience substantial positive (negative) abnormal returns for companies listed with positive (negative) potential on *CreditWatch prior* to the listing date. The pre-listing abnormal returns not only reflect the direction, but also the magnitude of rating changes on the delisting date. Second, equity markets exhibit little reaction to the delisting of a company from *CreditWatch*, even when the delisting is accompanied by a change in rating. Third, we find that the pre-listing abnormal returns in equity markets are good predictors of both the direction and the magnitude of the eventual change in credit. This is especially true for those firms listed with negative potential, which is by far the most common listing type. Collectively, our findings suggest that rating agencies may sacrifice timeliness for the sake of stability and that even *CreditWatch*, which is designed to mitigate the disadvantage caused by rating stability, is not a completely effective instrument.

If an advance notice service such as *CreditWatch* is already substantially anticipated by the market and too slow in conveying information, credit rating agencies may need to reconsider whether a policy of issuing stable ratings is too costly. In order to repair the reputational damage suffered during the 2007-2008 financial crisis, credit rating agencies must develop more effective measures to convey changes in default probability to the market in a timely manner.

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REFERENCES

- Altman, Edward, and Herbert Rijken, 2004, How rating agencies achieve rating stability, *Journal of Banking and Finance* 28, 2679-2714.
- Altman, Edward, and Herbert Rijken, 2006, The added value of rating outlooks and rating reviews to corporate bond ratings, Working Paper, New York University Salomon Center.
- Brister, Bill, Robert Kennedy, and Pu Liu, 1994, The regulation effect of credit ratings on bond interest yield: The case of junk bonds, *Journal of Business Finance and Accounting* 21, 511-531.
- Cantor, Richard, 2001, Moody's investors service's response to the consultative paper issued by the basel committee on bank supervision 'A new capital adequacy framework,' *Journal of Banking and Finance* 25, 171–185.
- Cantor, Richard, and Christopher Mann, 2003, Are corporate bond ratings procyclical? Moody's Special Comment (October).
- Cantor, Richard, and Christopher Mann, 2007, Analyzing the tradeoff between ratings accuracy and stability, Moody's Special Comment (Spring).
- Cheng, Mei and Monica Neamtiu, 2009, An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility, *Journal of Accounting and Economics* 47, 108-130.
- Dichev, D. Ilia and Joseph D. Piotroski, 2001, The long-run stock returns following bond ratings changes, *Journal of Finance* 5, 173-203.
- Goldstein, Morris, Graciela Kaminsky, and Carmen Reinhart, 2000, Assessing Financial Vulnerability: An Early Warning System for Emerging Markets, *Institute for International Economics*, ISBN 0-88132-237-7.
- Hand, John R.M., Robert Holthausen, and Richard Leftwich, 1992, The effect of bond rating agency announcements on bond and stock prices, *Journal of Finance* 47, 733-752.
- Holthausen, Robert and Richard Leftwich, 1986, An analysis of the informational value of bond rating changes, *Journal of Financial Economics* 17, 57-89.
- Hull, John, Mirela Predescu, and Alan White, 2004, The relationship between credit default swap spreads, bond yields, and credit rating announcements, *Journal of Banking and Finance* 28, 2789-2811.
- Jorion, Philippe and Gaiyan Zhang, 2007, Information effects of bond rating changes: The role of the rating prior to the announcement, *Journal of Fixed Income* 16, 45-60.

- Loffler, Gunter, 2005, Avoiding the rating bounce: Why rating agencies are slow to react to new information, *Journal of Economic Behavior and Organization* 56, 365-381.
- Morgan, Donald P., 2002, Rating banks: Risk and uncertainty in an opaque industry, *American Economic Review* 92, 874-888.
- Norden, Lars, and Martin Weber, 2004, Informational efficiency of credit default swaps and stock markets: The impact of credit rating announcements, *Journal of Banking and Finance* 28, 2565-2573.
- Reinhart, C.M., 2002, Credit ratings, default, and financial crises: Evidence from emerging markets. *World Bank Economic Review* 16, 151–170.
- Sy, Amadou, 2004, Rating the rating agencies: Anticipating currency crises or debt crises?, *Journal of Banking and Finance* 28, 2845-2867.
- Wansley, James W. and Terrence M. Clauretie, 1985, The impact of CreditWatch placement on equity returns and bond prices, *Journal of Financial Research* 8, 31-42.

Table I: Summary of CreditWatch Listings with Positive Potential

This table summarizes the frequency distribution by ratings of companies that were listed on the *CreditWatch* with "positive" potential between January 2002 and December 2005. The credit ratings on the very left column are the original ratings of companies immediately before the *CreditWatch* listing. The ratings on the top row are the new ratings after the removal (delisting) from the *CreditWatch* list. Ratings on the diagonal are companies whose ratings remain unchanged. Since this table contains only firms listed with "positive" potential, all the companies ended with rating upgrades (below the diagonal) or unchanged (on the diagonal) except one company (which was lowered from B+ to B-).

											R	ating Afte	er Delisti	ng									
		AAA	AA+	AA	AA-	A+	А	A-	BBB+	BBB	BBB-	BB+	BB	BB-	$\mathbf{B}+$	В	B-	CCC+	CCC	CCC-	CC	С	Total
	AAA	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	AA+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA-	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	A+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	А	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Listing	A-	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
List	BBB+	0	0	1	1	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	10
re]	BBB	0	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	7
Original Rating Before	BBB-	0	0	0	0	0	0	1	1	9	0	0	0	0	0	0	0	0	0	0	0	0	11
8	BB+	1	0	0	0	0	0	1	0	0	4	3	0	0	0	0	0	0	0	0	0	0	9
tin	BB	0	0	0	0	0	0	0	0	0	3	3	3	0	0	0	0	0	0	0	0	0	9
Ra	BB-	0	0	0	0	1	0	0	1	0	0	0	9	3	0	0	0	0	0	0	0	0	14
nal	B+	0	0	0	0	0	0	0	0	0	0	0	3	9	3	0	1	0	0	0	0	0	16
igi	В	0	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	0	0	0	0	5
Or	B-	0	0	0	0	0	1	0	0	0	0	0	0	2	3	2	1	0	0	0	0	0	9
	CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	3
	CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC-	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
	CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
	С	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1	0	2	1	2	4	9	11	9	7	6	16	15	11	2	4	0	0	0	1	0	101

Table II: Summary of	f CreditWatch	Listings with	Negative Potential

This table summarizes the frequency distribution by ratings of companies that were listed on the *CreditWatch* with "negative" potential between January 2002 and December 2005. The credit ratings on the very left column are the original ratings of companies immediately before the *CreditWatch* listing. The ratings on the top row are the new ratings after the removal (delisting) from the *CreditWatch* list. Ratings on the diagonal are companies whose ratings remain unchanged. Since this table contains only firms listed with "negative" potential, with the exception of five cases, all the companies ended with rating downgrades (above the diagonal) or unchanged (on the diagonal).

												Rating	After De	elisting										
		AAA	AA+	AA	AA-	A+	А	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	В	B-	CCC+	CCC	CCC-	CC	С	D	Total
	AAA	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	AA+	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	AA	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	AA-	0	0	0	3	8	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13
	A+	0	0	0	0	6	9	6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22
	А	0	0	0	0	0	9	18	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	30
00	A-	0	0	0	0	0	0	21	11	3	0	0	1	0	0	0	0	0	0	0	0	0	0	36
Listing	BBB+	0	0	0	0	0	0	0	17	14	4	1	1	0	0	0	0	0	0	0	0	0	0	37
Ľ.	BBB	0	0	0	0	0	0	0	0	20	23	5	2	0	0	0	0	0	0	0	0	0	0	50
ore	BBB-	0	0	0	0	0	0	0	0	0	25	26	9	4	0	0	0	0	0	0	0	0	0	64
Befo	BB+	0	0	0	0	0	0	0	0	0	1	11	20	2	3	1	0	0	0	0	0	0	0	38
l și	BB	0	0	0	0	0	0	0	0	0	0	0	19	28	11	1	1	0	0	0	0	0	0	60
Rating	BB-	0	0	0	0	0	0	0	0	0	0	0	0	21	21	4	3	0	0	0	0	0	0	49
IR	$\mathbf{B}+$	0	0	0	0	0	0	0	0	0	0	0	0	0	20	12	4	0	1	0	1	0	0	38
ginal	В	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	3	7	3	0	1	0	0	23
Orig	B-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	3	0	2	0	0	0	9
0	CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	0	0	5
	CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	2	0	1	5
	CCC-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	3	5
	CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	2	0	4	9
	С	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	0	3	3	5	15	19	46	32	38	53	43	52	55	55	27	16	12	6	7	8	0	8	503

Table III: Financial Characteristics of Firms Listed on CreditWatch

This table presents basic financial characteristics of the sample firms for the year prior to being listed on *CreditWatch*. Total Assets are presented in millions of dollars. ROA is computed as net income divided by total assets. The Debt Ratio is computed as total liabilities divided by total assets. The Cash Ratio is cash and cash equivalents divided by total assets. The days between listing and delisting is the number of calendar days between the listing and delisting dates. *, **, *** denotes statistically different from zero based on a standard t-test for the means and a Wilcoxon test for the medians at the 10%, 5% and 1% levels, respectively.

		Total Assets (\$MM)	ROA (%)	Debt Ratio (%)	Cash Ratio (%)	Days Between Listing and Delisting
				Firms with Positive Potenti	als	
	Mean	12,754	-4.05%	72.87%	10.90%	116.2
e)	5 th	461	-33.61	31.52	0.97	16.0
Percentile	25 th	1,387	-1.92	55.77	3.30	36.0
cen	Median	3,171	1.80	71.22	7.45	96.5
er	75 th	10,623	5.42	88.82	12.04	157.5
-	95 th	63,667	10.60	109.67	31.64	291.0
	Std. Dev.	22,298	32.82	29.09	12.22	91.2
	Ν	97	97	97	97	100
				Firms with Negative Potent	ials	
	Mean	25,600	-0.47%	69.60%	8.60%	102.1
9	5 th	611	-22.41	39.71	0.34	22.0
	25 th	2,074	-2.35	55.81	1.76	44.0
	Median	6,143	1.69	67.83	4.74	73.5
	75 th	16,604	4.56	82.37	11.44	134.0
-	95 th	103,914	11.31	102.08	28.31	275.0
	Std. Dev.	83,588	12.64	19.86	10.73	88.3
	Ν	486	486	486	486	498
	Difference of Means	-12,846***	-3.58	3.27	2.30*	14.1
	Difference of Medians	-13,433***	0.11	6.66	2.71***	23.0

Table IV: Equity Market Reaction to CreditWatch Listing

This table presents the mean values of the daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the listing day on *CreditWatch*. Results are presented separately based on the expected rating change potential (positive or negative) at the time of listing. The AR and CAR are calculated using three models as described in Section I: the market model (MKT), the market adjusted return model (MADJ), and the Fama-French 3-factor model (FF). *, **, *** denotes statistically different from zero based on a Patell z-test at the 10%, 5% and 1% levels, respectively.

AR		Firms	with Positiv	ve Pote	ntials			Firms	s with Nega	tive Pot	tentials	
Day	MKT Model		MADJ Model		FF Model		MKT Model		MADJ Model		FF Model	
-7	0.08%		0.26%		0.11%		-0.28%	**	-0.31%	**	-0.26%	
-6	-0.07%		-0.01%		-0.11%		-0.32%	***	-0.38%	***	-0.32%	***
-5	0.15%		0.39%		0.09%		-0.76%	***	-0.77%	***	-0.69%	
-4	0.34%	*	0.43%	**	0.36%		-0.24%	*	-0.32%	**	-0.24%	
-3	0.78%	***	0.78%	***	0.70%	**	-0.21%	*	-0.24%	*	-0.21%	***
-2	0.20%	**	0.34%	***	0.11%	**	-0.75%	***	-0.82%	***	-0.68%	**
-1	-0.10%		0.13%		-0.12%		-1.41%	***	-1.46%	***	-1.40%	***
0	2.71%	***	2.79%	***	2.67%	**	-2.83%	***	-2.84%	***	-2.86%	***
1	0.18%		0.27%		0.26%	*	-1.14%	***	-1.18%	***	-1.11%	***
2	0.01%		0.09%		0.03%		-0.24%	**	-0.26%	**	-0.27%	**
3	-0.05%		0.03%		0.01%		0.25%	*	0.20%		0.28%	
CAR		Firms	with Positiv	ve Pote	ntials			Firms	s with Nega	tive Pot	tentials	
Days	MKT Model		MADJ Model		FF Model		MKT Model		MADJ Model		FF Model	
(-60, -1)	3.78%	***	10.01%	***	2.89%	**	-7.11%	***	-10.82%	***	-7.08%	***
(-30, -1)	1.64%	**	4.85%	***	1.37%	*	-6.23%	***	-8.20%	***	-5.95%	***
(-7,-1)	1.39%	***	2.32%	***	1.16%		-3.97%	***	-4.32%	***	-3.80%	***
(0,0)	2.71%	***	2.79%	***	2.67%	**	-2.83%	***	-2.84%	***	-2.86%	***
(+1,+3)	0.13%		0.40%		0.29%		-1.13%	***	-1.24%	***	-1.10%	**
N	101		101		101		503		503		503	

Table V: Equity Market Reaction to CreditWatch Listing Categorized by Delisting Action

This table presents the mean values of daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the listing date on *CreditWatch* categorized by the change in rating that occurs when the firm is delisted. The AR and CAR are computed using the market model as described in Section I. The sample size is reduced because firms delisted with rating changes in an opposite direction of the initial listing are excluded from analysis. Separate results are presented for firms listed with positive and negative potential. Within the categories of positive (negative) potential, results are further classified by the magnitude of delisting action: affirmed with no change in rating, up (down) by one notch, up (down) by two notches, or up (down) by three or more notches. Abnormal returns generated by both the market adjusted return model and Fama-French 3-factor model produce qualitatively similar results and are not reported. *, **, *** denotes statistically different from zero based on a Patell z-test at the 10%, 5% and 1% levels, respectively.

AR				Pos	itive							Neg	ative			
Day	Affirmed		Up 1 Notch		Up 2 Notches		Up 3+ Notches		Affirmed		Down 1 Notch		Down 2 Notches		Down 3+ Notches	
-7	0.66%		0.14%		-0.17%		-0.76%		-0.07%		-0.25%	*	-0.88%	**	-0.21%	
-6	-0.32%		-0.12%		-0.55%		0.77%		-0.29%	**	-0.12%		-1.53%	***	0.39%	
-5	-0.06%		0.09%		0.90%	*	0.16%		-0.13%		-0.86%	***	-1.61%	***	-1.18%	*
-4	0.02%		0.01%		2.42%	***	0.35%		-0.02%		-0.46%	***	-0.03%		-0.23%	
-3	0.55%		0.34%	*	3.91%	***	0.31%		0.14%		-0.29%	**	-0.34%		-1.13%	
-2	-0.24%		0.00%		-0.42%		1.75%	***	-0.54%	***	-0.17%	**	-1.13%	***	-4.17%	***
-1	0.19%		-0.68%	*	1.41%	***	0.49%		-0.87%	***	-1.74%	***	-1.05%	***	-3.20%	***
0	4.84%	***	0.07%	**	4.24%	***	8.94%	***	-0.65%	**	-3.74%	***	-2.89%	***	-8.63%	***
1	0.48%		0.17%		-0.11%		0.00%		-0.78%	***	-0.80%	***	-1.43%	***	-3.95%	***
2	-0.14%		-0.18%		1.34%	**	0.04%		-0.29%		-0.45%	***	-0.30%		0.95%	
3	-0.77%		0.22%		0.23%		-0.30%		0.07%		0.03%		0.53%	*	1.51%	**
CAR				Pos	itive							Neg	ative			
Day	Affirmed		Up 1 Notch		Up 2 Notches		Up 3+ Notches		Affirmed		Down 1 Notch		Down 2 Notches		Down 3+ Notches	
(-60, -1)	7.53%	*	-0.48%		11.02%	***	6.36%	*	-1.83%	***	-7.68%	***	-12.66%	***	-23.69%	***
(-30, -1)	5.53%		-1.94%		9.84%	***	3.01%		-2.08%	***	-7.09%	***	-10.70%	***	-18.20%	***
(-7,-1)	0.80%		-0.23%		7.51%	***	3.07%	**	-1.78%	***	-3.88%	***	-6.58%	***	-9.72%	***
(0,0)	4.84%	***	0.07%	**	4.24%	***	8.94%	***	-0.65%	**	-3.74%	***	-2.89%	***	-8.63%	***
(+1,+3)	-0.44%		0.21%		1.46%		-0.26%		-0.99%	***	-1.22%	***	-1.19%	**	-1.50%	***
Ν	20		55		11		14		193		199		68		38	

Table VI: Equity Market Reaction to CreditWatch Delisting

This table presents the mean values of daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the date of delisting from *CreditWatch*. The AR and CAR are computed using the market model as described in Section I. The sample size is reduced because firms delisted with rating changes in an opposite direction of the initial listing are excluded from analysis. Separate results are presented for firms listed with positive and negative potential. Within the categories of positive (negative) potential, results are further classified by the magnitude of delisting action: affirmed with no change in rating, up (down) by one notch, up (down) by two notches, or up (down) by three or more notches. Abnormal returns generated by both the market adjusted return model and Fama-French 3-factor model produce qualitatively similar results and are not reported. *, **, *** denotes statistically different from zero based on a standard t-test at the 10%, 5% and 1% levels, respectively.

AR			Firms Listed	with	Positive Potenti	al					Firms 1	Listed	with Negative Po	otential		
Day	Affirmed		Up 1 Notch		Up 2 Notches		Up 3+ Notches		Affirmed		Down 1 Notch		Down 2 Notches		Down 3+ Notches	
-7	-3.31%	***	-0.58%		0.23%		-1.53%		0.01%		-0.37%	*	-1.49%	***	4.95%	***
-6	1.04%	**	0.18%	*	-0.49%		-1.66%	*	0.22%		-0.42%		-2.07%	***	1.05%	***
-5	-0.93%	***	-1.01%	**	-0.53%		-0.98%		-0.15%		-0.13%		0.43%		-1.22%	**
-4	-0.34%		0.63%		0.24%		-0.55%		0.19%		0.59%	*	0.33%		0.84%	
-3	0.10%		-0.42%		-0.38%		-0.43%		0.11%		0.57%	*	-0.85%	**	0.57%	**
-2	-0.20%		0.29%		0.18%		-1.84%		0.26%		-0.01%		0.01%		-2.98%	***
-1	-0.03%		-0.16%		-1.48%	*	1.18%		0.04%		0.35%	*	0.15%		-0.87%	
0	-0.55%		-0.62%	**	0.65%		-0.36%		0.28%		-0.07%		1.04%	***	-1.49%	***
1	0.56%		0.50%	*	0.64%		0.39%		0.10%		0.16%		-0.69%	**	0.94%	**
2	-0.26%		1.37%	*	-1.72%	**	-0.46%		0.13%		0.22%		-0.24%		0.12%	
3	0.07%		0.17%		-0.19%		-0.42%		0.22%		0.47%	**	-1.26%	**	2.29%	***
CAR			Firms Listed	l with	Positive Potenti	al					Firms l	Listed	with Negative Po	otential		
Day	Affirmed		Up 1 Notch		Up 2 Notches		Up 3+ Notches		Affirmed		Down 1 Notch		Down 2 Notches		Down 3+ Notches	
(-7,-1)	-3.66%	***	-1.07%		-2.23%		-5.82%	*	0.68%	*	0.59%		-3.50%	**	2.35%	
(0,0)	-0.55%		-0.62%	**	0.65%		-0.36%		0.28%		-0.07%		1.04%	**	-1.49%	***
(+1,+3)	0.37%		2.05%	*	-1.27%		-0.49%		0.44%		0.85%	*	-2.16%	**	3.35%	***
Ν	19		49		8		6		191		196		63		32	

Table VII: Predicting the Magnitude of Rating Change at Delisting

This table presents results of regressing rating changes at delisting on the CAR surrounding the listing date and other control variables. The dependent variable in all models is the numerical change in rating that occurs upon delisting from *CreditWatch*. An upgrade (downgrade) is reflected by a negative (positive) number. LIST_CAR(T_1, T_2) is the CAR computed using the market model from days T_1 to T_2 relative to the day listed on *CreditWatch*. SPAN is the number of days between listing and delisting. LIST_RATING is the numerical rating at the time of listing. NEAR_JUNK is a dummy variable equal to one for negatively listed firms with an initial rating of BBB+, BBB, or BBB-. NEAR_INVESTMENT is a dummy variable equal to one for positively listed firms with an initial variables are from the fiscal year ending prior to the listing date: LN(ASSETS) is the natural log of total assets, ROA is net income divided by total assets, DEBT_RATIO is total liabilities divided by total assets, CASH_RATIO is cash and equivalents divided by total assets. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variables Dating Change		Both Positiv	e and Negative		Positive	Negative
Dependent Variable: Rating Change	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Tobit	(6) Tobit
Intercept	0.426 ***	0.991 ***	0.993 ***	1.618 ***	1.905 ***	-0.330
LIST_CAR(-7,-1)	-1.604 ***	-1.644 ***	-1.863 ***	-1.515 ***	-1.345 ***	-1.248 **
$LIST_CAR(0,0)$	-3.006 ***	-2.456 ***	-2.445 ***	-2.151 ***	-2.076 ***	-1.987 ***
<i>LIST_CAR</i> (+1,+3)	0.177	0.284	0.282	0.278	0.171	-0.511
SPAN		-0.002 ***	-0.002 ***	-0.002 ***	-0.002 ***	-0.001
LIST_RATING		-0.030 **	-0.031 **	-0.035 *	-0.048 **	-0.032
NEAR_JUNK		0.253 **	0.294 **	0.310 **		0.383 ***
NEAR_INVESTMENT		-1.806 ***	-1.837 ***	-1.848 ***	-2.944 ***	
LIST_CAR(-7,-1)* NEAR_JUNK			1.660 *	2.066 **		1.271
LIST_CAR(-7,-1)* NEAR_INVESTMENT			-3.033	-2.827	-1.746	
LN(ASSETS)				-0.013	-0.009	-0.002
ROA				-0.305	-0.312	-0.025
DEBT_RATIO				-0.103	-0.245	-0.044
CASH_RATIO				0.276	-0.080	0.051
Year Dummy	No	No	No	Yes	Yes	Yes
R-Square	0.087	0.194	0.209	0.217	0.470	0.340
F-value	19.93 ***	21.58 ***	17.24 ***	11.1 ***		
Log Likelihood Ratio Statistics					243.96 ***	1241.21 ***
Ν	598	598	598	583	583	583
Equality of Coefficients (F-test)	Difference	Difference	Difference	Difference	Difference	Difference
$H_0: LIST_CAR(-7,-1) = LIST_CAR(0,0)$	1.402 ***	0.812	0.582	0.636	0.731	0.739

Table VIII: Ordered Probit Model

This table presents results of an ordered probit model that regresses rating changes at delisting on the CAR surrounding the listing date and other control variables. The dependent variable in all models is the numerical change in rating that occurs upon delisting from *CreditWatch*. An upgrade (downgrade) is reflected by a negative (positive) number. LIST_CAR(T₁,T₂) is the CAR computed from days T_1 to T_2 relative to the day listed on *CreditWatch*. SPAN is the number of days between listing and delisting. LIST_RATING is the numerical rating at the time of listing. NEAR_JUNK is a dummy variable equal to one for negatively listed firms with an initial rating of BB+, BBB, or BBB-. NEAR_INVESTMENT is a dummy variable equal to one for positively listed firms with an initial rating of BB+, BB, or BB-. Financial variables are from the fiscal year ending prior to the listing date: LN(ASSETS) is the natural log of total assets, ROA is net income divided by total assets, NEAF_RATIO is cash and equivalents divided by total assets. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Rating Change	Ordered Probit	Ordered Probit	Ordered Probit
Intercenter	(1)	(2)	(3)
Intercepts: Down 6 Notches	-2.940 ***	-2.555 ***	-2.324 ***
Down 5 Notches	-2.519 ***	-2.141 ***	-2.324 ***
Down 5 Notches	-2.050 ***	-1.668 ***	-1.424 ***
Down 3 Notches	-1.349 ***	-0.961 ***	-0.759 *
Down 2 Notches	-0.705 ***	-0.313 *	-0.084
Down 2 Notches	0.307 ***		-0.084 0.984 **
		0.755	
Affirmed	1.450	2.010	2.270
Up 1 Notches	2.109	2.194	5.007
Up 2 Notches	2.507	5.101	5.570
Up 3 Notches	2.033	3.377 *** 3.519 ***	5.700
Up 4 Notches	2.152	5.517	5.004
Up 5 Notches	2.911	3.706 ***	4.145 ***
Up 6 Notches	3.022 ***	3.843 ***	
Up 8 Notches	3.175 ***	4.037 ***	4.337 ***
LIST_CAR(-7,-1)	-0.895 ***	-0.963 ***	-1.235 ***
$LIST_CAR(0,0)$	-1.818 ***	-1.512 ***	-1.473 ***
$LIST_CAR(1,3)$	0.193	0.322	0.115
SPAN		-0.002 ***	-0.002 ***
LIST_RATING		-0.022 *	-0.029 **
NEAR_JUNK		0.242 **	0.291 ***
NEAR INVESTMENT		-1.458 ***	-1.469 ***
LIST_CAR(-7,-1)* NEAR_JUNK		11100	1.855 **
LIST_CAR(-7,-1)* NEAR_INVESTMENT			0.494
LN(ASSETS)			-0.009
ROA			-0.217
DEBT_RATIO			-0.106
CASH RATIO			0.124
Year Dummy	Yes	Yes	Ves
Teal Dunning	105	105	108
R-Square	0.11	0.22	0.25
AIC	1909.38	1835.78	1775.91
Ν	598	598	583
Equality of Coefficients (F-test)	Difference	Difference	Difference
H_0 : LIST_CAR(-7,-1) = LIST_CAR(0,0)	0.923 *	0.549	0.238

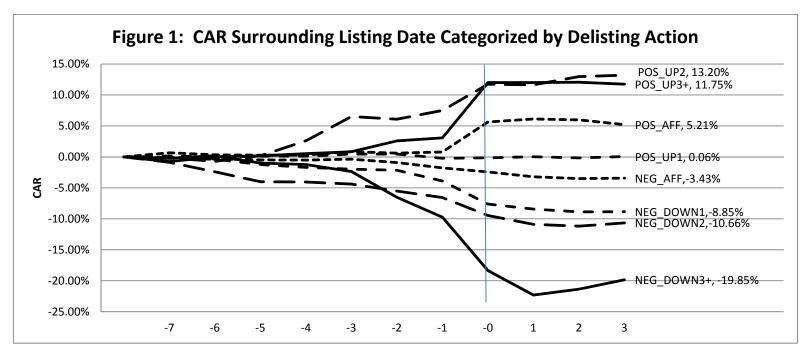
Table IX: Reaction to One-Notch Downgrade based on Initial Bond Quality

This table examines the effect of bond quality on the magnitude of daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the listing date. Abnormal returns are computed using the market model (MKT) as described in Section I. Downgraded by one notch samples are decomposed into different subgroups according to their original listing position. Variables are defined same as before. *, **, *** denotes statistically different from zero based on a standard t-test at the 10%, 5% and 1% levels, respectively.

AR			Downgrade-by-One-	Notch		
Day	Downgrade from A+ to A		Downgrade from BBB to BBB-		Downgrade from B+ to B	
-7	0.18%		-0.58%	*	-1.00%	
-6	-0.89%	**	-0.74%		-1.23%	
-5	0.23%		-0.67%		-3.21%	**
-4	-0.46%		-0.91%	**	-1.84%	**
-3	-0.68%		-0.64%		-1.38%	
-2	0.00%		-0.28%		2.96%	*
-1	-0.99%		-1.92%	***	-2.30%	***
0	-2.67%	***	-0.28%		-8.69%	***
1	-0.35%		0.26%		-3.17%	***
2	-0.38%		-0.81%	**	2.54%	**
3	-0.85%	*	0.33%		4.54%	***
CAR			Downgrade-by-One-	Notch		
Day	Downgrade from A+ to A		Downgrade from BBB to BBB-		Downgrade from B+ to B	
(-60, -1)	-2.19%		-8.97%	***	-19.52%	***
(-30, -1)	-3.73%		-7.91%	***	-13.37%	**
(-7,-1)	-2.62%	*	-5.74%	***	-8.00%	***
(0,0)	-2.67%	***	-0.28%		-8.69%	***
(+1,+3)	-1.57%	**	-0.22%		3.91%	
N.	10		23		12	

Figure 1: Cumulative Abnormal Returns Surrounding the Listing Date Categorized by Delisting Action

This figure presents the mean cumulative abnormal returns (CARs) surrounding the listing date (defined at t = 0) from seven days before to three days after the listing day (-7,+3), categorized by the delisting action. POS_AFF is listed with positive potential followed by rating affirmation (i.e. unchanged) upon delisting. POS_UP1, POS_UP2, and POS_UP3+ are listed with positive potential followed by upgrade of 1, 2, and 3 or more notches, respectively, upon delisting. NEG_AFF is listed with negative potential followed by rating affirmation upon delisting. NEG_DOWN1, NEG_DOWN2, and NEG_DOWN3+ are listed with negative potential followed by downgrade of 1, 2, and 3 or more notches, respectively, upon delisting.



Appendix I: Credit Rating Transformation

The following is the scale used to transform credit ratings from letters to numerical values, which is consistent with Morgan (2002). Note that the bonds with the highest (lowest) quality receive the lowest (highest) numerical score.

S&P's	Numerical
Credit Rating	Rating
AAA	1
AA+	2
AA	3
AA-	4
A+	5
А	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
В	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC	20
С	21
D	22

Appendix II: Industry Classification

This table summarizes the breakdown of industries represented in the sample by the first digit of the SIC code in Compustat.

1 st Digit SIC Code	Positive Potential	Negative Potential	Total	Percent of Total
0	0	2	2	0.34%
1	6	31	37	6.34
2	7	85	102	17.47
3	25	102	127	21.75
4	21	114	134	22.95
5	9	40	49	8.39
6	11	54	65	11.13
7	6	36	42	7.19
8	1	22	23	3.94
9	1	1	2	0.34
Total	97	487	584	