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The roles of rating outlooks: the predictor of creditworthiness and the monitor of recovery efforts

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Abstract

Using a comprehensive U.S. rating sample from S&P's between 1981 and 2015, we examine the information content, responsiveness to credit risk and recovery effort associated with rating outlooks. We find that rating outlooks (and credit watches) have important information contents and are significantly associated with credit worthiness, measured by expected default frequency. More importantly, we show that by assigning negative outlooks, credit rating agencies induce some issuers to exert recovery efforts to prevent subsequent downgrades. The finding supports the theoretical prediction of Boot et al. (2006) that credit rating actions serve as a coordination mechanism between rating agencies and issuers.

JEL Classifications: G14, G20, G24

Keywords: rating outlook; information content; credit risk; recovery effort

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1. Introduction

To supplement credit ratings, credit rating agencies (CRAs) use rating outlook (OL) together with review or credit watch (CW)[1] to indicate the views of CRAs in relation to the likelihood and direction of future rating changes. Many studies show the important roles of credit ratings in the capital market. Only a few studies (Holthausen and Leftwich 1986; Hand, Holthausen and Leftwich 1992; Chung, Frost and Kim 2012; Driss, Massoud and Roberts 2016; Liu and Sun 2017) investigate the information value and the impacts of credit watch. The role of rating outlooks has received eve less academic attention.

Major CRAs such as Moody's Investors Service (Moody's), Standard and Poor's Ratings Services (S&P's) and Fitch Ratings (Fitch) show that OL and CW indicate the likely directions of rating changes in near term. CW may lead to rating change within 90 days, and OL implies potential rating change in 18 to 24 months. Previous studies (Holthausen and Leftwich 1986; Bannier and Hirsch 2010; Chung, Frost and Kim 2012) confirm that CW contains information value; that is, both negative and positive CWs have significant market response surrounding the event dates. The information value of OL has not been investigated yet.

The empirical results of Hamilton and Cantor (2004) suggest that the distribution of credit rating changes and the future default conditional on ratings outlooks are likely to differ significantly from the conditional distributions for a given rating category using Moody's ratings data. CRAs suggest that OL and CW are valuable predictors of credit worthiness and

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[1] S&P's uses the term "credit watch" where Moody's adopts the term "rating under review" for issuers/ratings that are placed on the watchlist. As both terms essentially mean the same rating procedure, we simply use the term "credit watch" (CW) to refer to both.

subsequent rating changes (S&P 2005; Moody's 2008).

Boot, Milbourn and Schmeits (2006), (Boot's Model hereafter), theoretically argue that credit ratings serve as a coordinating mechanism between CRAs and the issuers. By assigning the issuers on negative CW list, CRAs enter an implicit contract with issuers agreeing to discuss the remedied actions with management and monitor the firms' progress in recovery effort. Chung, Frost and Kim (2012) find that firms do take some action in the period between negative watch and subsequent rating revisions. However, given the short time period on the watch list, that is, 90 days, it may be difficult for some firms to exert meaningful recovery efforts to avoid downgrades. We believe that negative OL may also induce firms to take remedial action to avoid downgrades, because negative OL also indicates potential downgrade and the outlook period can last as long as two years. For example, Moody's assigned a negative OL to Microsoft in 2016 with a rating action report (negative OL report hereafter) (see Figure 1). After about 16 months, Microsoft subsequently received a rating affirmation and an OL change to stable from negative in 2017 (Moody's 2017) upon company's significant improvement in the specific areas mentioned in Moody's negative OL report (Moody's 2016). It seems that the rationale behind Moody's assignment of the negative OL and the conditions for possible rating actions (downgrade or rating affirmation) stated in the previous negative OL report may induce Microsoft to exert meaningful recovery effort and thereby avoid rating downgrade.

[Insert Figure 1 here]

Although there are analytical claims by CRAs and theoretical argument such as Boot's Model for the importance of credit rating actions mentioned above, we believe that the roles of OL procedure by CRAs are empirically understudied for its importance, especially the frequency of OL actions is as high as rating change actions. We conjecture that OL assignments can provide important information contents to the market, predict default risk and induce recovery efforts of the corporate issuers[2]. Therefore, to fill this research gap, our empirical study has three major objectives by testing three hypotheses. First, we investigate the information content of OLs, that is, we examine the effects of negative and positive OLs on the stock returns (Informational Content Hypothesis). Second, we examine the predictive power of OLs on credit risk (Default Risk Hypothesis). Specifically, we analyze the effects of OL (and CW) on the changes of credit worthiness (instead of future rating changes) of the issuers where credit worthiness is measured by the expected default frequency following Bharath and Shumway (2008) and Xia (2014). Third, we test the recovery efforts undertaken by the firms with negative OLs (Recovery Effort Hypothesis). That is, we test the hypothesis that a firm is more likely to attain rating confirmation after negative outlook if it exerts more recovery efforts, and we compare the recovery efforts undertaken by the firms with negative OL assignments and those without. This is a very timely study especially when CRAs are subject to strong criticisms for not being timely or informative[3].

We use a comprehensive U.S. rating sample from S&P's between 1981 and 2015 to test the information content, responsiveness to credit risk and recovery effort of rating outlook. The results are summarized as follows. First, negative rating outlooks (and credit watches) have significant information content. The average three-day cumulative abnormal return surrounding event dates is -1.09% for negative outlooks. We do not find significant market response to positive outlooks. The results are consistent with the literature that the positive actions by CRAs may be anticipated by the market. Second, the assignments of rating outlook and credit watch are significantly associated with the credit worthiness, measured by expected

[2] Boot, Milbourn and Schmeits (2006) conjecture that credit watch procedure can induce firms to exert recovery efforts to avoid downgrades and rating outlook should be considered as a refinement of firms' ratings (see Footnote 15 in their paper). In our empirical study, we examine whether both CW and OL are associated with future default risk (the role of refinement of credit ratings) and whether negative OL is associated with subsequent improvements in financial strength of the firm (the role of inducing recovery effort).

[3] CRAs are criticized for assigning unreasonably high ratings to structured products before the financial crisis. With respect to corporate bonds, Hung, Banerjee and Meng (2017) show that, because of slow revisions of credit ratings by CRAs, the firms facing downgrades would issue more debts in order to take advantage of current higher ratings.

default frequency. Negative outlook/watch predicts the increase of subsequent default probability, while positive outlook/watch is responsive to the decrease of default risk.

Lastly, we confirm the recovery effort hypothesis that CRAs induce, at least, some of the issuers to take necessary actions to prevent subsequent downgrades through rating outlook process. Recovery efforts are measured in different dimensions of corporate performance, such as the improvements in interest coverage and profitability, the reductions in corporate leverage, and the use of short-term debt and capital expenditure. We find that these recovery efforts, exerted in the interval between negative outlook and subsequent rating action, are positively associated with the likelihood that the issuers receive rating confirmation (instead of downgrade). In comparison to the firms of the same rating grade but without negative OL, the issuers receiving negative OL assignments and subsequent confirmations do show significant improvements in the corporate fundamentals during the OL period. However, we find that the fundamentals of firms with negative OL assignments and subsequent downgrade deteriorate during the OL assignment periods; and the difference of the changes in the fundamentals between these firms and the firms with direct downgrade are not significant. Overall, the finding supports the theoretical prediction of Boot et al. (2006) that credit rating acts as a coordination mechanism between CRAs and some of the issuers.

Our study contributes to the literature in the following distinctive ways. This is the first study to confirm the information value conveyed by corporate issuers' OL which is lacking in the literature. Despite the important economic functions and significant informational contents of OL and CW of corporate issuers suggested by CRAs, there are only a few academic studies on OL and CW (not along with rating changes); and, the research effort with empirical work devoted to ratings outlooks is even scarce[4]. Further, we show that both OL and CW are

[4] Hill and Faff (2010), and Alsakka and ap Gwilym (2012) analyze OL and CW of sovereigns, not corporate issuers. Finnerty, Miller and Chen (2013) focus on the impact of credit rating announcements on credit default swap spreads.

significant predictors of an issuer's credit worthiness, which have not yet been documented in the literature. Most importantly, our study is the first academic study to confirm the coordination mechanism by CRAs through the rating outlook process. Our results are consistent with the predictions of Boot et al. (2006) that CRAs supply information to the capital market, monitor the issuers by placing them on the outlook list, and guide them to make recovery to prevent downgrades when their credit qualities are possibly deteriorating. Boot's Model argues that the coordination mechanism becomes effective through credit watch process. We conjecture that the coordination occurs in the outlook process too. The findings of our study are important and relevant to regulators and market participants who perform monitoring roles and make investment decisions based on credit rating actions including CW and OL.

The paper is structured as follows. Section 2 presents the background of the research and the existing literature on rating outlook and credit watch. Section 3 describes the hypotheses, research methodology, data and sample for this study. The empirical results are discussed in Section 4, followed by the conclusions in Section 5.

2. Background of Research

2.1 Rating Outlook and Credit Watch

All three major CRAs, Moody's, S&P's and Fitch, adopt outlook and watchlist procedures (Moody's 2004; Fitch 2005; S&P's FS 2011). According to Fitch's Special Report, "A Rating Outlook indicates the direction in which a rating is likely to move over a one- to two-year period. Outlooks may be Positive, Stable or Negative." (Fitch 2005). Sixty-two percent of Fitch's sovereign ratings with a negative or positive outlook have subsequently been downgraded or upgraded, compared to 24% of sovereign ratings with a stable outlook during the period 2000-2005.

Referring to S&P's FS (2011), 'If S&P's anticipates that a credit rating may change in the coming 6 to 24 months, it may issue an updated ratings outlook indicating whether the possible change is likely to be “positive”, “negative”, “stable”, or “developing” (meaning it’s uncertain whether a rating might go up or down). Or, if events or circumstances occur that may affect a credit rating in the near term, usually within 90 days, S&P’s may place the rating on CreditWatch.

Moody’s defines OL as “an opinion regarding the likely direction of an issuer’s credit quality, therefore its rating, over the medium term, usually an average ex-ante horizon of 18 months. Rating outlooks take the values positive, negative, stable and developing” and “rating reviews are a subset of rating outlooks that are much stronger statements about the future directions a credit rating may take” (Moody’s 2004). Similar to S&P’s, Moody’s prefers to conclude rating reviews within 90 days, although it is not always possible (Moody’s, 1998).

In summary, these major CRAs use OL and CW to supplement credit rating actions. CW is usually placed for shorter term (within 90 days), while OL is often used for a medium term up to 18 or 24 months. Among the three major agencies, S&P’s has the longest history to assign OL and CW to issuers, starting in 1981. Moody’s formally gave the assignments of OL and CW starting in 1991.

2.2 Literature on credit ratings actions

There is an abundance of research on the information contents of credit rating actions by CRAs, but the majority of them relate to rating changes (that is, downgrades and upgrades), not to CW and OL. Starting with Holthausen and Leftwich (1986) and Hand, Holthausen and Leftwich (1992), some extant studies analyze the informational contents of CW and/or OL but they mostly relate to CW (e.g., Bannier and Hirsch 2010; Chan et al. 2011; Chung, Frost and Kim 2012; Liu et al. 2012; and Liu and Sun 2017). Hull, Predescu and White (2004), Norden and Weber (2004), and Finnerty, Miller and Chen (2013) investigate the relation between credit default swap spreads and credit rating announcements including rating changes, CW and OL changes. Kiesel and Kolaric (2018) compare the effects of watch-preceded rating changes and direct rating changes on CDS spread. The impact and signaling effect of both CW and OL are examined in Altman and Rijken (2007), Hill and Faff (2010), Alsakka and ap Gwilym (2012), and Finnerty, Miller and Chen (2013). Except for sovereign rating studies, the information content of OL on corporate issuers is not explored in the previous literature.

Some studies confirm that OL and CW are useful indications of likely rating changes in the future. Hill, Brooks and Faff (2010) find that CW and OL have significant predictive powers on sovereign rating changes for 129 countries from three major CRAs. Alsakka and ap Gwilym (2012) compare the assignment behaviors of CW and OL by three major CRAs. Altman and Rijken (2007) investigate "added value" of outlooks and reviews to corporate bond ratings in terms of improving the rating timeliness and default prediction performance based on U.S. evidence before the two recent financial crises. Hirsch and Krahnen (2007) is the only paper that directly tests the impacts of CW and OL on issuer default risk. They find that CW is significantly associated with the default risk expectation, measured by the distance to default (expected default frequency) from Merton (1974) model.

Boot, Milbourn and Schmeits (2006) discuss a novel rationale for the roles of credit rating in capital market and indicate that credit ratings serve as a "focal point" for issuers and the institutional investors. They believe that credit ratings derive their value primarily from two institutional features: (1) the *monitoring role* of CRAs which is most apparent in their credit watch procedures; and (2) the role of credit ratings in the investment decision of institutional investors. They also generate several empirically-testable predictions that relate to the CW procedure, the firm's initial credit quality, and the feasibility of recovery effort. In particular, with respect to the informational content of rating watch procedure, they suggest that rating changes occurring after a CW procedure will be more informative than those in the absence of a credit watch. For the recovery effort, they mention the importance of *contracting role* of CRAs through CW procedure. That is, whenever the CRA observes potential changes in issuers' characteristics, it will request clarifications from the management. The rating is then often put on watchlist. The issuer will usually be asked to provide information on how to cope with the possible changes. Under such circumstances, the issuer implicitly commits to undertake specific actions (the recovery effort) to alleviate the potential adverse consequences of the change.

Bannier and Hirsch (2010), Chan et al. (2011), Chung, Frost and Kim (2012), and Liu and Sun (2017) empirically test the predictions of Boot's Model using Moody's CW data of U.S. issuers for different study periods (from 1982 to 2008). The results of these studies are mixed in support of the predictions of Boot's Model. Bannier and Hirsch (2010) test the roles of delivering information and implicit-contracting in CW procedure by investigating the agency's decision to assign CW, the CW duration, and the market reactions to watch-preceded and direct downgrades. They argue that the results support both explanations of information content and coordinating mechanism of CW. However, the results of Chan et al. (2011), only favor the explanation of information supplying but not coordination role of CW. Both papers test Boot's Model by examining the market response to rating actions rather than directly testing the recovery efforts given by the issuers to improve their corporate fundamentals. Chung, Frost and Kim (2012) identify the recovery efforts from the rating confirmation news after negative CW. In 309 negative watch cases, recovery efforts such as reducing financial risk and improving income/liquidity are found in 162 cases.

Instead of testing the recovery efforts in watch period, Liu and Sun (2017) find that the firms with watch-preceded downgrades exert more recovery efforts in post-downgrade period than firms with direct downgrades. Their findings suggest that watch procedure induces remedial actions after the firms are downgraded, which is consistent with the recovery effort predictions in Boot's Model. In addition to Boot's Model, the theoretical work by Manso (2013) also highlights the importance of the impact of credit rating actions on the issuer's recovery effort. Manso (2013) shows that CRAs should focus on the rating accuracy and on the effects of their ratings on the probability of survival of borrower due to feedback effects.[5] Our study differs from previous empirical studies in recovery efforts as we focus on the OL procedure. Despite its importance in the rating process, to our knowledge, there are very few studies that investigate its role with respect to recovery efforts and default risk.

3. Hypotheses development, methodology and sample

3.1 Hypotheses development and methodology

We propose three hypotheses related to the roles of OL (and CW) in the rating process: (1) conveying information, (2) predicting default risk, and (3) inducing issuer's recovery efforts. According to the claims by CRAs, all rating actions including OL, CW and rating changes convey information to the market. Many studies confirm that rating changes and CW significantly affect stock prices, bond yields and CDS spreads (e.g. Hull, Predescu and White 2004; Norden and Weber 2004; Galil and Soffer 2011; Chou 2013; Salvade 2018; Luo and Chen 2019). On the contrary, other studies find that CW, OL or rating changes do not reveal new information to the market for the credit rating announcements that are triggered by public events. CRAs do not have advantages in corporate credit quality in comparison with other investors (Boot, Milbourn and Schmeits 2006; page 96).

Chung, Frost and Kim (2012) indicate that CW is more likely triggered by publicly known events. They also find that CW results in significant abnormal stock returns due to the role of credit watch in allowing issuers to make corrections and avoid potential downgrade. In this

[5] According to Manso (2013), "Rating agencies are supposed to provide an independent opinion on the credit quality of issuers. However, if market participants rely on credit ratings for investment decisions, then credit ratings themselves affect the credit quality of issuers". This is called "feedback effects" of credit ratings.

context, the information carried by CW does not contain credit quality information, but contains the private information involving a firm's potential efforts to resolve the rating deterioration. However, it is still questionable whether OL would play the same role as CW with respect to private information. Hence, we develop the following hypotheses.

Hypothesis 1: Informational Content Hypothesis

H1: Both OL and CW contain informational contents (have significant market response).

We use the event study methodology to investigate the impacts of CW and OL on stock prices. We calculate cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR) for both CW and OL rating actions. Abnormal return is the difference between realized return and expected return given in the market model; CAR is the cumulative abnormal return across an event window; and, BHAR is the difference between the realized buy-and-hold return and the normal buy-and-hold return across an event window. Similar to previous studies (Holthausen and Leftwich 1986; Hand, Holthausen and Leftwich 1992; Bannier and Hirsch 2010), we choose a three-day event window spanning from day -1 to day +1. The estimation window starts from day -120 to day -20, with the condition of a minimum of 70 daily stock returns in the window. We use the value-weighted return of all US firms from CRSP as market return. As some rating actions of OL and CW are accompanied with rating changes, we report the market reactions to the full sample of OL/CW and the pure sample of OL/CW without rating changes[6].

The second hypothesis tests whether OL and CW are useful predictors of credit worthiness and default risk. Previous studies in sovereign credit ratings (Hill, Brooks and Faff 2010;

[6] Starting from Holthausen and Leftwich (1986), the studies in credit rating exclude the credit events overlapped with corporate news surrounding the event window (contaminated events). The relevant corporate news is normally selected from some sources like Wall Street Journal. However, Galil and Soffer (2011) argue that the practice of excluding contaminated events leads to selection-bias, and that the market responses by uncontaminated sample are underestimated. Given that the credit events of OL and CW may not have strong market reaction, we do not exclude the contaminated events as to better estimate the impacts of OL and CW.

Alsakka and ap Gwilym 2012) suggest that both OL and CW imply the subsequent rating changes. Previous studies (Loffler, 2013; Xia 2014; Kedia et al. 2014) show that credit ratings are informative indicators of default risks. Since CRAs claim that both OL and CW are indicative for the subsequent rating changes, we hypothesize that OL and CW are also responsive to default risk. The hypothesis is given as follows.

Hypothesis 2: Default Risk Hypothesis

H2: Both OL and CW are significantly associated with default risk of the issuers. Negative OL/CW predicts the increase of default probability, while positive OL/CW predicts the decrease of default probability.

Following prior studies (Vassalou and Xing 2004; Bharath and Shumway 2008; Liu and Sun 2017; Bao and Liu 2018; Liu, Luo and Han 2019), we calculate the expected default frequency (EDF) from Merton's model (Merton 1974) to measure the probability of default. The equity value is treated as call option on a firm's total assets, where a firm goes default when the market value of total assets is less than its liability. The EDF is the probability that firm value falls below the liability in the following one year, which is computed from market value of equity, the volatility of stock price, the face value of debt, risk free rate, and a time period of one year using an iterative procedure[7]. We obtain monthly EDF for each issuer, calculate the change of EDF[8] in a month, and use Equation (1) to test the default risk hypothesis.

$$\Delta EDF_{i,t} = \alpha_0 + \beta_1 OL_{i,t} + \beta_2 CW_{i,t} + \beta_3 DOWN/UPGRADE_{i,t} + \beta_4 RATING_{i,t} + \beta_5 X_{i,t} + Industry_j + Year_t + \varepsilon_{i,t} \quad (1)$$

[7] There are several steps used to calculate the expected default frequency according to the Merton model. The first step is to estimate the volatility of equity return from historical stock price, and to calculate the face value of the debt in a firm as the sum of current liabilities and 50% of the long-term debt. The key step is to estimate the volatility of firm's asset value and the market asset value based on Merton model from the equity volatility, the face value of debt, risk-free rate and time to maturity (Equations (2) and (5) in Bharath and Shumway (2008)). The expected default frequency is the one minus cumulative probability that the firm value is higher than the face debt value (Equation (7) in Bharath and Shumway (2008)). More details can be found in Bharath and Shumway (2008).

[8] We appreciate referees' suggestions to adopt the change of EDF as dependent variable to test H2. In our earlier version, EDF was used as dependent variable and find that OL or CW assignment significantly affects the level of expected default risk.

The dependent variable in Equation (1) is ΔEDF computed following Merton's model, as actual corporate default cases are scarce. The variables OL and CW are dummies equal to 1 if the firm is on outlook and watch lists in the month. Following the literature of credit ratings, we estimate the impact of negative and positive OL/CW separately. DOWNGRADE (UPGRADE) is a dummy variable equal to 1 if the firm is downgraded (upgraded) in the month. The variable RATING is the numerical value assigned to the letter grade of credit ratings. Similar to Xia (2014) and Kedia et al. (2014), we incorporate some control variables into the equation including leverage ratio, operating profitability, market-to-book ratio, tangibility ratio, the volatility of leverage during the past eight quarters, and the volatility of operating profitability during the past eight quarters. We include industry and year dummies in the regressions. Industry dummy is created based on two-digit SIC codes. We expect that the coefficients of OL and CW are significant and positive (negative) for the negative (positive) OL/CW.

The last hypothesis tests the predictions of coordination mechanism in Boot's Model. In the original model, Boot et al. (2006) argue that CRAs use watch procedure as an implicit contract to induce the recovery efforts. However, the watch period normally lasts only for 90 days, which may be too short for issuers to take remedial action. We extend Boot's Model to outlook procedure and expect that after the assignments of negative OLs, issuers can exert recovery efforts to prevent future downgrades. Recovery efforts are observed from the corporate financial variables that can affect credit quality and used by CRAs to justify credit ratings (S&P's FS 2011; Liu and Sun 2017). The more the issuers conduct recovery efforts in the outlook period, the less the probability of subsequent downgrades will be. In addition, we also expect that regardless whether the issuers with negative OLs subsequently receive rating confirmations or downgrades, their corporate fundamentals are improved in comparison to the firms of the same rating level but without preceded negative OLs or with direct downgrade.

This result confirms that the recovery effort is indeed induced by the negative OL assignment[9].

We propose the hypothesis as follows.

Hypothesis 3: Recovery Effort Hypothesis

H3a: After CRAs have assigned negative OLs to issuers, the issuers with more recovery efforts to restore credit quality are more (less) likely to receive rating confirmations (downgrades).

H3b: After CRAs have assigned negative OLs to issuers, the issuers that eventually receive rating confirmations have more improvements in corporate fundamentals than the issuers with the same rating level but without negative OLs.

H3c: After CARs have assigned negative OLs to issuers, the issuers that are eventually downgraded have more improvements in corporate fundamentals than the issuers with direct downgrades.

We focus on the firms with negative outlooks to test this hypothesis. Following S&P's rating reports (S&P's FS 2011) and Liu and Sun (2017), a set of firm characteristic variables including interest coverage (INTCOV), leverage (LEV), short-term debt to total debt (STDTTD), returns on assets (ROA), and capital expenditure (CAPEX) are used to measure corporates' recovery efforts. The improvements in these firm characteristics reflect the recovery efforts during the period that firms are placed on the OL list. To quantify recovery efforts, we compare these corporate variables in the pre-OL assignment periods (from four quarters before negative OL assignment to assignment quarter) and the post-OL assignment period (between the OL assignment quarter and OL resolution quarter). The time frame of the empirical analysis is shown in Figure 2.

[Insert Figure 2 here]

After measuring recovery efforts, we test Hypothesis H3a by exploring whether the issuers receiving rating confirmations undertake more recovery efforts than those receiving

[9] Liu and Sun (2017) find that the firms receive negative watches and subsequent downgrades have better improvements in the financial strength than the firms with direct downgrades. However, the improvements of the firms with negative credit watches in their paper are measured after they are downgraded. Hence, the improvements may not be attributed to the recovery efforts in response to credit watch assignments. Our Hypothesis H3 explores the recovery efforts that the issuers undertake to avoid potential downgrades after negative OLs, which is more relevant to Boot et al. (2006).

downgrades after negative OL assignments and whether these improvements can prevent subsequent downgrades using logistic regression function. The dependent variable CONFIRM is a dummy variable equal to 1 if the negative OL is resolved with rating confirmation, and 0 if it is followed by downgrade. The key variable RECOVERY is a set of variables that indicates the improvement of corporate fundamentals between the pre-OL assignment and the post-OL assignment periods. We expect the coefficients of RECOVERY variables to be positive. Some corporate variables that may affect the rating confirmation decision by CRAs are included in the function: rating level, investment grade, firm size, market-to-book, cash ratio, and tangibility. We also include industry and year dummies. The regression function is given in Equation (2).

$$CONFIRM_{i,t+1} = \alpha_0 + \beta_1 RECOVERY_{i,t} + \beta_2 RATING_{i,t} + \beta_3 INVESTGRADE_{i,t} + \beta_4 X_{i,t} + Industry_j + Year_t + \varepsilon_{i,t} \quad (2)$$

We then test Hypotheses H3b and H3c by comparing the changes in the corporate fundamentals between the issuers receiving negative OLs and those with no rating action or direct downgrades. The matching approach is applied to test the hypotheses following Liu and Sun (2017). The issuers with negative OLs are divided into two treatment groups: (1) issuers with rating confirmations and (2) issuers with downgrades. The control group for the first group of treated issuers are the firms that have the same rating level as the treated observations with stable outlook (i.e., similar issuers without negative OLs) in the past three years. In the quarter when a firm with negative OL assignment receives rating confirmation, we match it to a firm from the control group by rating grade, industry and firm size in the same quarter. After matching, the control issuer is assigned a pseudo negative OL assignment quarter as the treated issuer. The changes in the corporate fundamentals for the control issuer are then calculated on the basis of pseudo negative OL assignment. If the improvements are much larger in the treatment group than that of the control group, we can confirm that the recovery effort is induced by the negative OL.

The matching process is similar for the second group of treated issuers, i.e., issuers with negative OL and subsequent downgrades. For the treatment group of the issuers subsequently receiving downgrade in a quarter, we match each treated firm with a firm with direct downgrade in the same quarter by rating level after downgrade, industry and firm size. The control issuer is assigned with a pseudo negative OL quarter from the matched treated issuer. If the recovery firms are induced by negative OLs to exert recovery efforts, we should observe the significant differences of the changes in the corporate fundamentals between the treatment group and the control group.

The detailed variable definitions are in Appendix 1.

3.2 Data and sample description

Our sample starts with all US issuers with S&P's long-term issuer credit ratings and their corresponding OLs and CWs during the period 1981-2015[10]. We choose 1981 as the starting year of the sample because that is the year S&P's began to provide rating actions of OL and CW. We obtain all rating actions and related data from S&P's *RatingsDirect Global Credit Portal* (S&P's FS 2016). We convert the letter grades of ratings into numerical values, where AAA=22, AA+=21, ..., and D=1. The conversions can be found in Appendix 2.

We refine the raw data with the requirement that the issuer should have financial statement data from Compustat or stock data from CRSP. Table 1 reports the frequencies of rating actions by year. The final sample contains 9,414 outlooks, 6,528 watches, and 11,781 rating changes from 1981 through 2015[11]. Similar to the observation in Chung, Frost and Kim (2012), the

[10] We choose S&P's data for several reasons. First, S&P's has longest history to release credit actions of OL and CW. The OL and CW sample by S&P is more comprehensive than the sample from Moody's or Fitch. Second, Hill and Faff (2010)'s study of sovereign OL and CW shows that S&P's tends to be more active, provide more timely rating assessments, and offer more new information than Fitch and Moody's. Also, other existing related studies have used mainly Moody's data. Our study can complement to current credit rating literature, especially the information content of OL and CW. We believe that our major conclusions still apply to the samples from Moody's or Fitch.

[11] In addition to negative and positive views of OL and CW, CRAs also give stable outlook (11,391 actions), developing outlook (330 actions) and developing watch (642 actions). We do not report the frequencies of these

ratios of OL and CW in total rating actions increase substantially from 1980s, which indicates the increasingly important role of these two procedures in the overall rating process. Interestingly, OL actions are more frequently used by CRAs than CW actions. According to our sample, there are 6,339 negative OL and 4,618 negative CW. It seems that OL should play at least as important a role as CW in the rating process; however, the study of the impact of OLs is scarce.

[Insert Table 1 here]

We extract the financial information including financial statement data and market data of these issuers from Compustat and CRSP. We use daily stock price data to calculate the abnormal returns, CAR and BHAR associated to the rating events. Following Bharath and Shumway (2008), we employ monthly stock price data and quarterly financial statement data to calculate the monthly default probability EDF. The variables of recovery efforts and corporate control variable are constructed using quarterly financial statement data.

[Insert Table 2 here]

Table 2 reports the summary statistics of the abnormal returns, default probability, recovery efforts, and control variables. The average CAR and BHAR for all rating actions (OL, CW and rating change) are -0.15% and -0.20%. The average expected default frequency in each month during the sample period is 18.48%. The percentages of downgrades and upgrades in one month are 1.48% and 0.99%, respectively. The percentages that the issuers are put on the negative OL and positive OL lists are 15.96% and 9.85% of the periods between 1981 and 2015. The percentages of negative and positive CWs are smaller, only 6.36% and 2.80% of the sample period. The average rating value in one month is 12.6906, which falls between the letter grades BB+ and BBB-.

actions in the table as CRAs argue that these actions do not indicate certain directions of future rating changes.

Among 5,651 negative outlooks[12] in the sample to test recovery effort hypothesis, 53.58% outlooks are resolved with rating confirmation. We measure the recovery effort through improvements in issuer credit quality in different firm characteristics mentioned above,[13] where the positive values of recovery effort variables indicate more recovery efforts. During the recovery period (between the OL assignment quarter and OL resolution quarter), the interest coverage ratio decreases by 2.1369, leverage ratio increases by 3.22%, and ROA decreases by 0.30%, which indicate poor recovery efforts on average. The short-term debt to total debt ratio decreases by 0.52%, and the ratio of capital expenditure to total assets decreases by 0.60%, indicating that the issuers take remedial actions to reduce short-term debt and capital expenditure.

4. Empirical results

4.1 Market reaction to OL and CW

This section presents market reactions to rating actions by event studies. Table 3 reports the cumulative and the buy-and-hold abnormal returns of OL and CW. Panel A shows that the average CARs and BHARs are significantly negative for total negative outlook events, pure negative outlook events, and negative outlook events accompanied with rating changes (mainly downgrades). On average, the CAR and BHAR for total negative outlooks are -1.09% and -1.17%, respectively, while the abnormal returns shrink to -0.66% and -0.71% in the sample of pure negative outlooks. The negative outlooks overlapped with rating changes have much stronger market responses than pure negative outlooks as the CAR and BHAR are -1.95% and

[12] The number of negative outlooks (5,651) for the test of recovery effort hypothesis is less than the total number of negative outlooks (6,336) reported in Table 1. The reason is that some negative outlooks are resolved immediately in the quarter that the issuers are put on the OL list. These outlooks are deleted as the recovery efforts cannot be detected from the changes of quarterly financial statement variables.

[13] The improvements include the increases of interest coverage ratio and ROA, as well as and the decreases of leverage ratio, short-term debt to total debt and capital expenditure.

-2.08%, respectively. Although these market reactions should be mainly attributed to downgrades, we find that negative outlook still conveys significant information to the market according to the significant results of the pure negative outlook sample.

[Insert Table 3 here]

Panel B of Table 3 shows the results of positive outlooks in the full sample and the pure sample. The average CAR and BHAR for the rating actions of pure positive outlook are 0.10% and 0.09%, respectively. The market reactions are not significant in the sample of pure positive outlook or the positive outlook with rating changes. The finding is consistent with the most literature that states rating upgrades do not have significant information content.

Panels C and D show credit watches have similar patterns of market reaction as rating outlooks. Negative watches have significantly negative abnormal returns. The average CAR and BHAR for total negative watches are -0.99% and -1.13%, respectively, and average CAR and BHAR are only -0.40% and -0.50% for pure negative watches. The market response is much stronger if the negative watch is accompanied with a rating change (mainly downgrade). The information value is also significant for positive watches, in which the average CAR and BHAR are as high as 3.57% and 3.53% in the pure sample. The results are similar to the previous studies on market reactions to credit watch announcements[14] (Hand, Holthausen and Leftwich 1992; Chan et al. 2011; Chung, Frost and Kim 2012; Kiesel and Kolaric 2018). Overall, the results confirm the information content hypothesis that both OL and CW (especially the negative actions) provide information value to the market. To the best of our knowledge, this study is the first to show significant market price impacts of OL for corporate issuers.

[14] It is worth to note that our CW sample is much larger than the previous studies. The sample in Chung, Frost and Kim (2012) has totally 1911 negative watches and 963 positive watches; Kiesel and Kolaric (2018) analyze 1526 watchlist placement announcements; the number of negative watches is 611 in Chan et al. (2011); and the numbers of firms with negative watches and positive watches are 104 and 23 in Hand, Holthausen and Leftwich (1992).

We further explore the information content of rating changes, that is, downgrades and upgrades with respect to CW/OL procedure. Specifically, we test whether the information values differ in the rating changes with and without CW/OL procedures. Boot et al. (2006) predict that the downgrades proceeded by negative CW are more informative than those in the absence of CW procedure because the watch-preceded downgrades signal the failure of the issuers' recovery effort. Panel A of Table 4 shows that the magnitude of price reactions for watch-preceded downgrades (-2.73% CAR and -2.68% BHAR) is smaller than those in direct downgrades (-3.25% CAR and -3.13% BHAR). However, the outlook-proceeded downgrades have stronger negative price effect (-3.83% CAR and -4.64% BHAR) than direct downgrades. These findings may indicate that it is OL procedure rather than CW procedure that serves as the coordination mechanism in the credit rating process. The market responses are not significant for direct upgrades or watch-proceeded upgrades, but only for outlook-preceded upgrades. The finding is consistent with the previous literature that upgrades do not convey new information to the market (Holthausen and Leftwich 1986; Hand, Holthausen and Leftwich 1992).

[Insert Table 4 here]

4.2 OL and CW as predictors of credit worthiness

Hamilton and Cantor (2004) suggest that OL and CW help alleviate the tension between rating accuracy and rating stability, the two major objectives of the credit rating system. Credit ratings are not adjusted for temporary changes in credit quality that may be reversed in the near term (Altman and Rijken 2004). OL and CW help mitigate the tension between the two objectives by providing timely warnings of likely rating changes that will follow if expectations are realized. Moody's report (Moody's 2005) indicates that the accuracy of Moody's ratings as predictors of default is improving by adjusting for outlook status. We expect that the assignments of OL and CW by CRAs reveal the changes of credit worthiness of issuers. The default risk in our study is measured by the expected default frequency (EDF) from Merton's model.

Figure 3 shows the average monthly EDFs of firms from 12 months before to 12 months after the month of downgrades, negative OLs, and negative CWs. Panel A gives the EDFs in the group of firms that receive downgrade after negative events in the following one year; and Panel B shows the EDFs in the group of firms without subsequent downgrade. The EDFs are found to have increased in a one-year period before firms receive downgrade, negative OL and negative CW, which indicates that the outlook and watch events are assigned due to the deterioration in credit quality. Panel A indicates that the default risk continues to increase or maintains at the same level in the six-month period after the negative events if the firms receive a subsequent downgrade. Panel B shows that the default probability reaches the peak in the month of negative events and starts to decrease afterwards in the firms without subsequent downgrade, which is consistent with the finding in Loffler (2013) and Liu and Sun (2017). The decrease of default risk may indicate that firms may have taken some considerable actions to restore credit quality after the negative OLs or CWs in an attempt to avoid possible downgrade.

[Insert Figure 3 here]

Figure 4 shows the average EDFs of firms from 12 months before to 12 months after the month of positive rating events. We also divide the sample into two groups: firms with subsequent upgrade within one year and firms without. The EDFs are found to have decreased in a one-year period before firms receive upgrades, positive OLs and positive CWs. It indicates that positive OLs and CWs are assigned when an issuers' credit worthiness improves. Panel A shows that the expected default probability remains similar in the following year after the month that firms receive positive rating actions if they are further upgraded. Panel B indicates that default risk increases in the following year if there is no subsequent upgrade, which shows that credit quality does not substantially improve in these firms after the after positive OL or

CW event.

In sum, we find increases (decreases) of default risks in the periods after negative (positive) OL and CW assignments if there are subsequent downgrades (upgrades) in the firms. The decreases of EDFs after negative OL assignments in some firms may be brought about by the recovery efforts in these firms in an attempt to avoid further downgrades. One important point to note is that these are raw descriptive figures without the control of rating levels or other firm fundamentals.

[Insert Figure 4 here]

We test whether the firms that are downgraded or upgraded and placed on OL or CW list are associated with changes in credit worthiness through Equation (1)[15]. Table 5 presents the predictive abilities of rating changes, OL and CW on subsequent default risks. The results in Column 1 indicate that the changes of expected default probabilities significantly increase by 1.08% in the month of downgrade; and the increases of expected default probabilities are 1.51% and 2.18% per month, respectively, during the periods that the firms are placed on negative OL and CW lists. The coefficients of downgrade, negative OL and negative CW are all significant at the 1% level.

The regression in Column 2 replaces the variable of credit rating by the financial statement variables that could affect firm credit worthiness. Similarly, the coefficients of dummy variables downgrade, negative OL and negative CW are positive and highly significant.

Column 3 of Table 5 shows that EDFs significantly decrease further by 0.59%, 0.66% and 1.42% per month if firms receive subsequent upgrades, positive OL assignments, and positive

[15] As the dummy variables downgrade (upgrade), negative (positive) OL and negative (positive) CW are included in the same regression model, one potential concern is that some of these variables may be highly correlated. Therefore, we have computed the correlations among rating change, credit watch and rating outlook in the sample. The correlation matrix of these variables shows that the correlations between each pair of these variables are less than 6%. Also, the variance inflation factors (VIFs) of the model with all these variables are less than 1.5. Therefore, the collinearity is found not a serious problem in Equation (1). The results remain similar if each variable of rating actions is included in the model one at a time.

CW assignments, respectively. Positive OLs and CWs are associated with larger decreases of default probabilities than upgrades. The low responsiveness of default risk to upgrades is consistent with the existing literature that states upgrades are anticipated by the market (Holthausen and Leftwich 1986; Hand, Holthausen and Leftwich 1992). Column 4 presents the results with the corporate control variables. The major results remain unchanged in both Columns 3 and 4.

[Insert Table 5 here]

We run several robustness tests to confirm the responsiveness of default risk to OL and CW assignments. First, we use the level of EDF as dependent variable in Equation (1). We find that the level of EDF significantly increases in the month that a firm is downgraded, assigned negative OL or CW; and the EDF significantly decreases in the firms with upgrade, positive OL or CW assignments. The results indicate that the rating action such as OL or CW is associated with credit risk in a firm. Second, as Bharath and Shumway (2008) argue that the expected default frequency from the Merton model may not be a sufficient measure for a firm's default. We use the failure probability method from Campbell, Hilscher and Szilagyi (2008) as an additional measure for credit risk. We calculate the failure probability for a firm in a month from the 12-month logistic regression (Campbell, Hilscher and Szilagyi 2008; Table IV). We find similar results that the rating actions including OLs and CWs are significantly associated with the level or change of default risk of a firm measured by its failure probability. The results are not reported to conserve the space but available upon request[16].

In sum, our results indicate that expected default risk is strongly associated with OL and CW assignments. We find that, in general, default risks significantly increase in the periods when firms are placed on negative OL and CW assignment lists, and decreased during positive OL and CW assignment periods. The magnitude of the changes of default risk per month in the

[16] We thank the suggestions of robustness tests from the referees.

OL and CW assignment periods is even larger than those changes induced by downgrade and upgrade. The results confirm our second hypothesis that OL and CW are valuable predictors of credit worthiness.

4.3 Negative OL and recovery efforts

We have shown that OL plays similar role as CW in providing information contents to the market and predicting future default risk. Boot et al. (2006) argue that in addition to processing information, CRAs coordinate the behaviors of firms and the beliefs of the market. Through the credit watch procedure, CRAs form an implicit contract with a firm and induce the firm to take remedial action to prevent subsequent downgrade. Boot et al. (2006) do not consider the outlook procedure in the coordination mechanism. However, we expect that OL would play a similar role as CW in inducing firms to undertake recovery efforts as both OL and CW indicate possible downgrades in the future, and OL gives longer time to firms than CW to take specific actions.

We employ difference-in-differences tests to explore the differences in the changes of corporate fundamental, that is, liquidity, debt financing, profitability and investment, before and after OL assignments in the groups of firms receiving rating confirmations and downgrades, and in the groups of firms with negative OLs and their corresponding matched firms. Table 6 provides the comparison results between the firms with rating confirmation and with downgrade after negative OL assignments. Panels A and B show the difference before and after OL assignments for the firms with negative OLs, followed by rating confirmations and downgrades, respectively. Both groups have significant decreases in interest coverage, increase in leverage and decrease in capital expenditure in post-OL assignment period. The firms with subsequent rating confirmations use less short-term debt and become more profitable in the post-OL assignment period while the firms with subsequent downgrades have increase in the short-term debt ratio and decrease in ROA.

Panel C of Table 6 presents the difference-in-differences results. The results show that the firms with rating confirmations (rating-confirmed firms) significantly outperform the downgraded firms in terms of some corporate financial fundamental variables. Examining the corporate variables related to credit quality, these rating-confirmed firms decrease less in interest coverage, increase less in leverage, decrease more in short-term debt, increase more in ROA, and decrease more in capital expenditure, than firms without rating confirmations (non-confirmed firms). The results provide evidence on recovery efforts that rating-confirmed firms improve their corporate fundamentals to improve the credit quality and avoid subsequent downgrades.

[Insert Table 6 here]

Table 7 presents the estimates of Equation (2) to test whether undertaking recovery efforts in the post-OL assignment period leads to rating confirmations. As indicated above, recovery effort is measured by the improvements in corporate fundamentals between pre-OL assignment period and post-OL assignment period, that is, increases in average interest coverage and ROA, decreases in average leverage, short-term debt, and capital expenditure. Columns 1 through 5 show the results using each of the recovery effort variables in the logistic regression function. The coefficients on recovery effort are all significant in these models. The results indicate that if a firm exerts efforts to maintain high interest coverage, reduce leverage and short-term debt, increase profitability and decrease capital expenditure, it is more likely to receive a rating confirmation. Column 6 combines all recovery effort variables in one regression model. The results remain similar, except that the coefficient of recovery effort variable by capital expenditure is not significant. The findings are consistent with the results in Table 6 and confirm Hypothesis H3a that if a firm with negative OL assignment exerts recovery efforts, it is highly likely to avoid downgrade subsequently.

[Insert Table 7 here]

We further test Hypotheses H3b and H3c to establish the casual link between negative OL assignments and recovery efforts. We match the issuers that are assigned negative OLs and subsequently receive rating confirmations to the firms that have the same rating grade but without negative OL. Similarly, we match the issuers that are assigned negative OLs and receive subsequent downgrades to the firms that are directly downgraded to the same rating level. The matching procedure guarantees that the firms in the treatment and control groups have similar properties except the negative OL assignment. If negative OLs cannot trigger any recovery efforts, we expect not to observe any significant difference in the changes of corporate fundamentals between treatment groups and control groups.

[Insert Table 8 here]

Table 8 reports the comparison of results between the issuers with negative OL assignments as well as subsequent rating confirmations and the matched issuers without negative OL assignment. In total, there are 396 pairs of matched firms. Panel A shows that issuers in the treatment group are found to have significant decreases in short-term debts and the capital expenditure and an increase in ROA after the negative OL assignments. The results of the matched sample are similar to those in the full sample reported in Panel A of Table 6. For the control group in Panel B, the changes in corporate fundamentals are generally not significant except that the average leverage ratio has significantly decreased after the pseudo negative OL assignment. The improvement in corporate fundamentals are generally absent in the control firms without negative OL assignments. Panel C shows that in term of the reductions in short-term debt and capital expenditure and the increase of ROA, the firms with negative OL assignments have significantly more improvements than the control sample. The results confirm Hypothesis H3b that negative OL assignment induces firms to exert the recovery efforts as to avoid subsequent downgrade.

To explore the potential recovery effort of the firms with negative OL assignments and followed by downgrades, we compare the changes in the corporate fundamentals between these firms and their corresponding matched firms with direct downgrades. Table 9 presents the results from 151 matched pairs. Panel A shows that for the firms receiving negative OLs with subsequent downgrades, the fundamentals continue to deteriorate after OL assignments except reduction in capital expenditure. Similar patterns are observed in Panel B from the firms with direct downgrades. The differences in the changes of fundamentals are not statistically significant between these two groups, which reject Hypothesis H3c. The results suggest that firms with poor fundamentals might not attempt to restore the credit quality even though they are given reasonable time to do so before being downgraded by CRAs. The negative OL assignment cannot induce recovery effort in these firms possibly because the credit quality is already difficult to repair.

[Insert Table 9 here]

Our study is the first to study the recovery effort by firms through the credit quality- related corporate variables and to confirm the coordination mechanism of CRAs through OL procedure. Unlike previous studies that explore recovery effort by market reactions to failed or successful efforts (Bannier and Hirsch 2010; Chan et al. 2011), we present direct evidence on the recovery effort and its impacts on subsequent rating actions. We also conduct some robustness tests (not reported but are available upon request) as follows. First, the recovery effort is measured by the improvements in corporate fundamentals between OL assignment quarter and post-OL assignment periods. Second, we use other credit quality related variables that are adopted by CRAs to measure recovery effort such as debt to EBITDA, cash flow from operations to debt, operating profitability, and operating margin. The results remain similar in these tests. In sum, we find that negative OL assignments can trigger the recovery efforts in some firms to avoid downgrades. However, the recovery efforts are absent in the firms that are eventually downgraded by CRAs.

5. Conclusion

In our study, we examine the roles of OL procedure in the credit rating process, namely, providing information to the market, predicting default risk, and inducing recovery efforts. We find that negative OLs (as well as CW) convey significant information to the market. The assignments of OL and CW are significantly associated with the changes of default risk, which indicates that they are useful predictors of issuers' credit worthiness. More importantly, we find that OL procedure also serves as a coordination mechanism between CRAs and firms. Specifically, CRAs induce firms to conduct recovery efforts through negative OL assignments to avoid future downgrades. Our results confirm that the firms that exert more recovery efforts are more likely to receive rating confirmation. OL procedure allows some firms to undertake specific actions to improve credit quality.

OL procedure is understudied in the credit rating literature, although the frequency of OL actions by CRAs is as high as rating change actions. This is a timely study especially when CRAs are subject to strong criticisms for not being timely or informative. Our study indicates that both OL and CW have information contents and are associated with default risk. CRAs use them to improve rating accuracy, and meanwhile maintain rating stability. The monitoring role of CRAs in the capital market is not thoroughly studied. Bonsall, Koharki and Neamtiu (2015) find that CRAs relax the monitoring role after giving the initial credit rating to asset securitizations. However, our study finds that CRAs can continuously monitor issuers through the OL procedure. We believe that CRAs can add value to the capital market through both information supplying and monitoring activities.

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Table 1: Frequencies of outlook, watch and rating action by year

	Outlook action		Watch action		Rating change	
Year	**Negative**	**Positive**	**Negative**	**Positive**	**Downgrade**	**Upgrade**
1981	1	3	6	1	37	44
1982	2	0	4	0	65	28
1983	2	2	5	2	45	44
1984	7	0	8	6	53	53
1985	7	4	18	10	73	42
1986	15	11	31	12	112	58
1987	32	22	44	17	83	72
1988	113	64	38	18	91	98
1989	108	59	51	20	84	93
1990	135	58	53	19	148	65
1991	107	46	45	22	133	66
1992	100	58	63	35	86	112
1993	115	75	46	39	84	153
1994	103	81	49	19	96	109
1995	150	131	116	76	116	157
1996	136	129	139	112	123	166
1997	149	153	140	106	126	200
1998	246	122	252	137	206	187
1999	255	94	312	141	311	168
2000	326	97	279	75	409	121
2001	385	73	353	71	483	122
2002	398	75	337	42	524	113
2003	346	92	261	58	343	160
2004	244	166	195	79	210	176
2005	233	163	237	97	253	183
2006	244	167	247	118	209	210
2007	272	134	209	96	257	196
2008	498	102	322	35	472	165
2009	528	93	233	63	521	165
2010	155	185	83	87	156	280
2011	158	146	99	74	171	260
2012	202	132	92	41	182	190
2013	131	114	48	86	141	264
2014	150	132	100	53	134	234
2015	283	95	103	43	284	206
Total	6,336	3,078	4,618	1,910	6,821	4,960

Table 2: Summary statistics

Variable	N	Mean	Median	Std. Dev.	Min	Max
Variables for H1 information content hypothesis:						
CAR	18,157	-0.0015	-0.0016	0.0586	-0.1324	0.1320
BHAR	18,157	-0.0020	-0.0020	0.0587	-0.1337	0.1316
Variables for H2 default risk hypothesis:						
EDF	252,243	0.1848	0.0001	0.3354	0	1
ΔEDF	249,505	0.0005	0	0.0920	-0.9990	1
DOWNGRADE	252,243	0.0148	0	0.1206	0	1
UPGRADE	252,243	0.0099	0	0.0990	0	1
NEGOL	252,243	0.1596	0	0.3662	0	1
POSOL	252,243	0.0985	0	0.2980	0	1
NEGCW	252,243	0.0636	0	0.2441	0	1
POSCW	252,243	0.0280	0	0.1650	0	1
RATING	252,243	12.6906	13	3.6440	1	22
LEV	230,494	0.3512	0.3212	0.2102	0	1.1226
OPROFIT	220,186	0.0311	0.0300	0.0244	-0.0636	0.1280
MTB	232,728	1.5495	1.2925	0.8026	0.7414	6.9410
TANG	233,690	0.3272	0.2696	0.2636	0	0.9088
SALES	246,607	6.0247	6.0132	1.4388	0.2263	9.6014
LEVGVOL	245,837	0.0448	0.0292	0.0493	0	0.3355
OPROFITVOL	227,481	0.0111	0.0072	0.0137	0.0003	0.1163
Variables for H3 recovery effort hypothesis:						
COMFIRM	5,651	0.5358	1	0.4988	0	1
DINTCOV	2,494	-2.1369	-0.1527	19.9587	-345.7205	162.8359
DLEV	3,398	-0.0322	-0.0116	0.1079	-1	0.6721
DSTDTTD	3,380	0.0052	0.0005	0.1705	-1	1
DROA	3,581	-0.0030	-0.0007	0.0276	-0.1672	0.1498
DCAPEX	3,354	0.0060	0.0015	0.0262	-0.2464	0.1905
INVESTGRADE	5,651	0.4318	0	0.4954	0	1
SIZE	4,660	7.9508	7.8476	1.6219	3.0876	11.8995
CASH	4,650	0.0714	0.0374	0.0940	0.0000	0.6721

Table 3: Stock market response to outlook and watch actions

This table presents cumulative abnormal return (CAR) and buy-hold abnormal return (BHAR) that surround the OL and CW issue dates. The abnormal returns are calculated from market model; and, the event window is three days (-1, +1) surrounding the event date. We include the events that have at least 70 daily returns in the estimation window from day -120 to day -20. Panels A and B give the abnormal returns for negative and positive OL events. Panels C and D present the abnormal returns for negative and positive CW events. Outlook and watch actions may be overlapped with credit rating change on the event date. Total sample consists of all available OL or CW events (positive or negative), and pure sample contains outlook or watch actions that are not accompanied by rating changes. We report the number of observations, the abnormal returns and t statistics in the table. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

	N	CAR	t-stat	BHAR	t-stat
Panel A: Negative outlook					
Total negative outlook	3521	-0.0109***	10.42	-0.0117***	11.15
Pure negative outlook	2335	-0.0066***	5.50	-0.0071***	5.92
Negative outlook with rating change	1186	-0.0195***	9.67	-0.0208***	10.33
Panel B: Positive outlook					
Total positive outlook	1997	0.0009	0.95	0.0008	0.80
Pure positive outlook	1705	0.0010	1.02	0.0009	0.90
Positive outlook with rating change	292	0.0000	0.02	-0.0002	0.07
Panel C: Negative watch					
Total negative watch	2582	-0.0099***	6.43	-0.0113***	7.31
Pure negative watch	2009	-0.0040**	2.35	-0.0050***	2.96
Negative watch with rating change	573	-0.0307***	8.82	-0.0333***	9.54
Panel D: Positive watch					
Total positive watch	1209	0.0336***	16.36	0.0332***	16.20
Pure positive watch	1135	0.0357***	16.63	0.0353***	16.46
Positive watch with rating change	74	0.0020	0.37	0.0016	0.30

Table 4: Stock market response to rating change actions

This table presents cumulative abnormal return (CAR) and buy-hold abnormal return (BHAR) that surround downgrade and upgrade dates. The abnormal returns are calculated from market model; and the event window is three days (-1, +1) surrounding the event date. We include the events that have at least 70 daily returns in the estimation window from day -120 to day -20. Panel A presents the abnormal returns from downgrade samples, including total downgrades, direct downgrades, downgrades preceded by negative OL, and downgrades preceded by negative CW. Panel B presents the abnormal returns from upgrade samples, including total upgrades, direct upgrades, upgrades preceded by positive OL, and upgrades preceded by positive CW. We report the number of observations, the abnormal returns and t statistics in the table. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

	N	CAR	t-stat	BHAR	t-stat
Panel A: Downgrade					
Total downgrades	3527	-0.0323***	7.46	-0.0347***	14.67
Direct downgrades	821	-0.0325***	5.95	-0.0313***	6.36
Negative outlook preceded downgrades	1231	-0.0383***	3.46	-0.0464***	11.00
Negative watch preceded downgrades	1475	-0.0273***	7.62	-0.0268***	7.74
Panel B: Upgrade					
Total upgrades	2917	0.0017*	1.89	0.0017*	1.79
Direct upgrades	1244	0.0025	1.52	0.0025	1.47
Positive outlook preceded upgrades	1068	0.0018*	1.60	0.0018*	1.53
Positive watch preceded upgrades	605	-0.0002	0.11	-0.0003	0.19

Table 5: Predictive abilities of rating change, outlook and watch on credit risk

This table presents the estimates of OLS regressions in Equation (1). The sample period starts from 1981 to 2015. The dependent variable is the change of expected default frequency (ΔEDF). EDF is calculated from Merton's model, which measures a firm's default probability in the following period of one year. DOWNGRADE/UPGRADE is a dummy variable equal to 1 if the firm is downgraded/upgraded in the month; NEGOL/NEGCW is a dummy variable equal to 1 if the firm is placed on negative OL/CW list in the month; POSOL/POSCW is a dummy variable equal to 1 if the firm is placed on positive OL/CW list in the month; and, RATING is numerical value of credit rating in the month. Corporate control variables include: leverage (LEV), operating profitability (OPROFIT), market to book ratio (MTB), tangibility (TANG), sales (SALES), the volatilities of leverage (LEVGVOL) and operating profitability (OPROFITVOL). These control variables are in lagged term. Industry and year dummies are included in the regressions. Variable definitions are contained in Appendix 1. Robust-corrected *t*-statistics are reported in in parentheses. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Variable	(1)	(2)	(3)	(4)
DOWNGRADE	0.0108***	0.0089***		
	(4.21)	(3.27)		
NEGOL	0.0151***	0.0139***		
	(5.72)	(4.90)		
NEGCW	0.0218***	0.0192***		
	(7.50)	(6.22)		
UPGRADE			-0.0059***	-0.0059***
			(-3.62)	(-3.31)
POSOL			-0.0066***	-0.0049**
			(-3.54)	(-2.43)
POSCW			-0.0142***	-0.0137***
			(-4.63)	(-4.04)
RATING	0.0002***		0.0001	
	(2.58)		(1.15)	
LEV		-0.0081***		-0.0074***
		(-5.52)		(-5.03)
OPROFIT		-0.0614***		-0.0689***
		(-4.89)		(-5.49)
MTB		0.0025***		0.0024***
		(8.87)		(8.42)
TANG		0.0016		0.0019
		(1.03)		(1.24)
SALES		-0.0006***		-0.0006***
		(-3.36)		(-2.98)
LEVGVOL		0.0020		0.0025
		(0.31)		(0.38)
OPROFITVOL		-0.0190		-0.0118
		(-0.90)		(-0.56)
Constant	-0.0021**	0.0042***	-0.0002	0.0044***
	(-2.33)	(2.73)	(-0.19)	(2.85)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N of obs.	244,618	193,571	244,618	193,571
Pseudo R-squared	0.0202	0.0220	0.0189	0.0210

Table 6: Recovery effort by firms on negative outlook list

This table presents the differences of credit quality related variables before and after negative OL assignment for firms receiving rating confirmation subsequently in Panel A and for firms receiving downgrade subsequently in Panel B, and the difference in differences between the two groups in Panel C. The credit quality variables include interest coverage (INTCOV), leverage (LEV), short-term debt to total debt (STDTD), return on assets (ROA), and capital expenditure (CAPEX) in quarterly basis. Pre-OL assignment period is from four quarters before negative OL assignment to assignment quarter. OL quarter is the negative OL assignment quarter. Post-OL assignment period is between the negative OL assignment quarter and OL resolution quarter. We report average values of the variables in the period, the differences, the number of observations, and *t*-statistics in the table. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Periods	**INTCOV**	**LEV**	**STDTTD**	**ROA**	**CAPEX**
A. Negative outlooks followed by rating confirmation:					
Pre-OL assignment period	7.3714	0.3738	0.1595	-0.0012	0.0350
OL assignment quarter	5.3259	0.4087	0.1543	-0.0055	0.0318
Post-OL assignment period	6.1307	0.3986	0.1427	0.0002	0.0286
Post - Pre	-1.2408**	0.0248***	-0.0169***	0.0014**	-0.0063***
t-stat	2.45	10.83	4.69	2.79	11.06
N	1743	2314	2306	2466	2322
B. Negative outlooks followed by downgrade:					
Pre-OL assignment period	6.7920	0.4051	0.1570	-0.0035	0.0352
OL assignment quarter	3.4956	0.4482	0.1747	-0.0162	0.0325
Post-OL assignment period	3.4329	0.4479	0.1683	-0.0127	0.0297
Post - Pre	-3.3591***	0.0428***	0.0114**	-0.0092***	-0.0054***
t-stat	5.23	13.97	2.32	11.38	7.41
N	1601	2071	2067	2223	2098
C. Difference-in-difference:					
Diff. Post - Pre (A - B)	2.1183**	-0.0180***	-0.0282***	0.0106***	-0.0009
t-stat	2.62	4.81	4.76	11.59	0.98

Table 7: The impacts of recovery effort on the rating confirmation decisions for the firms with negative outlook

This table presents the estimates of logistic regressions in Equation (2). The sample contains 5,651 firm-quarter observations from 1981 to 2015. The dependent variable is rating confirmation (CONFIRM), a dummy equal to 1 if a negative OL is resolved with rating confirmation. Recovery effort is measured by the improvements of corporate fundamentals from pre-OL assignment period to post-OL assignment period, including increase in interest coverage (DINTCOV), decrease in leverage (DLEV), decrease in short-term debt (DSTDTTD), increase in ROA (DROA), and decrease in capital expenditure (DCAPEX). RATING is numerical value of credit rating in the quarter of outlook assignment; INVESTGRADE is a dummy equal to 1 if the rating is in the category of investment grade. Corporate control variables include: total assets (SIZE), market to book ratio (MTB), cash ratio (CASH), and tangibility (TANG). These control variables are in the OL assignment quarter. Industry and year dummies are included in the regressions. Variable definitions are contained in Appendix 1. Robust-corrected *t*-statistics are reported in in parentheses. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
DINTCOV	0.0073***					0.0051*
	(2.71)					(1.90)
DLEV		2.6114***				2.4152***
		(5.24)				(3.83)
DSTDTTD			1.0048***			1.1629***
			(3.84)			(3.36)
DROA				15.8317***		14.0443***
				(8.03)		(6.27)
DCAPEX					2.9061*	1.8826
					(1.78)	(0.99)
RATING	-0.1029***	-0.1298***	-0.1204***	-0.1180***	-0.0963***	-0.1626***
	(-3.26)	(-5.00)	(-4.66)	(-4.58)	(-3.68)	(-4.69)
INVESTGRADE	0.3519*	0.3990**	0.3967**	0.3751**	0.3580**	0.5034**
	(1.85)	(2.42)	(2.42)	(2.31)	(2.17)	(2.51)
SIZE	0.2357***	0.2359***	0.2450***	0.2142***	0.1951***	0.2742***
	(4.61)	(5.62)	(5.80)	(5.19)	(4.63)	(4.96)
MTB	0.6924***	0.7040***	0.6223***	0.6403***	0.6001***	0.8144***
	(4.15)	(4.22)	(3.83)	(4.22)	(3.88)	(4.64)
CASH	0.7130	1.0038*	1.0357*	0.6701	0.7597	0.8298
	(1.03)	(1.78)	(1.82)	(1.19)	(1.43)	(1.08)
TANG	-0.3325	-0.1026	-0.2504	-0.2992	-0.2327	-0.2709
	(-1.02)	(-0.35)	(-0.87)	(-1.05)	(-0.81)	(-0.79)
Constant	-1.0776	-0.9941	-1.0997	-0.4669	-0.8550	-0.4553
	(-1.34)	(-1.35)	(-1.45)	(-0.64)	(-1.11)	(-0.56)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N of obs.	2121	2830	2821	2935	2759	2050
Pseudo R-squared	0.1122	0.1038	0.0995	0.1187	0.0980	0.1545

Table 8: Negative outlook and recovery effort to avoid downgrade

This table presents the differences of credit quality related variables before and after negative OL assignment for firms with negative OL and receiving rating confirmation subsequently in Panel A (the treatment group) and for firms with the same rating level but without negative OL in Panel B (the control group), and the difference in differences between the two groups in Panel C. The control group are the firms that have the same rating level as the treated observations. In the quarter when a firm with negative OL assignment receives rating confirmation, we match it to a firm from the control group by rating grade, industry and firm size in the same quarter. After matching, the control issuer is assigned a pseudo negative OL assignment quarter as the treated issuer. There are 396 pairs after the matching. The credit quality variables include interest coverage (INTCOV), leverage (LEV), short-term debt to total debt (STDTD), return on assets (ROA), and capital expenditure (CAPEX) in quarterly basis. Pre-OL assignment period is from four quarters before negative OL assignment to assignment quarter. OL quarter is the negative OL assignment quarter. Post-OL assignment period is between the negative OL assignment quarter and OL resolution quarter. We report average values of the variables in the period, the differences, the number of observations, and *t*-statistics in the table. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Periods	**INTCOV**	**LEV**	**STDTTD**	**ROA**	**CAPEX**
A. Rating confirmation preceded by negative OL (treatment group):					
Pre-OL assignment period	10.0541	0.3320	0.1809	0.0051	0.0350
Post-OL assignment period	10.2032	0.3308	0.1684	0.0073	0.0292
Post - Pre	0.1491	-0.0012	-0.0125**	0.0021***	-0.0058***
t-stat	0.10	1.23	2.25	2.83	4.56
N	241	376	372	396	363
B. Rating without preceded OL/CW action or rating change (control group):					
Pre-OL assignment period	12.2355	0.3415	0.1498	0.0098	0.0326
Post-OL assignment period	12.6964	0.3360	0.1561	0.0100	0.0315
Post - Pre	0.4609	-0.0055**	0.0063	0.0002	-0.0012
t-stat	0.23	2.30	0.42	0.27	0.98
N	238	366	364	391	351
C. Difference-in-difference:					
Diff. Post - Pre (A - B)	-0.3119	0.0043**	-0.0189**	0.0019*	-0.0047***
t-stat	0.24	2.35	2.04	1.94	2.86

Table 9: Negative outlook and recovery effort in downgraded firms

This table presents the differences of credit quality related variables before and after negative OL assignment for firms with negative OL and receiving downgrade subsequently in Panel A (the treatment group) and for firms with the direct downgrade but without negative OL in Panel B (the control group), and the difference in differences between the two groups in Panel C. For the treatment group of the issuers subsequently receiving downgrades in a quarter, we match each treated firm with a firm with direct downgrade in the same quarter by rating level after downgrade, industry and firm size. The control issuer is assigned with a pseudo negative OL quarter from the matched treated issuer. There are 151 pairs after the matching. The credit quality variables include interest coverage (INTCOV), leverage (LEV), short-term debt to total debt (STDTD), return on assets (ROA), and capital expenditure (CAPEX) in quarterly basis. Pre-OL assignment period is from four quarters before negative OL assignment to assignment quarter. OL quarter is the negative OL assignment quarter. Post-OL assignment period is between the negative OL assignment quarter and OL resolution quarter. We report average values of the variables in the period, the differences, the number of observations, and *t*-statistics in the table. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Periods	**INTCOV**	**LEV**	**STDTTD**	**ROA**	**CAPEX**
A. Downgrade preceded by negative outlook (treatment group):					
Pre-OL assignment period	5.0481	0.3818	0.1518	0.0015	0.0388
Post-OL assignment period	2.6750	0.3966	0.1557	-0.0079	0.0330
Post - Pre	-2.3731**	0.0148***	0.0039	-0.0094***	-0.0058**
t-stat	2.25	3.46	0.65	4.23	2.35
N	97	139	139	151	138
B. Direct downgrade (control group):					
Pre-OL assignment period	6.8932	0.3809	0.1753	0.0020	0.0403
Post-OL assignment period	4.3141	0.4110	0.1914	-0.0066	0.0363
Post - Pre	-2.5791**	0.0301***	0.0161*	-0.0086***	-0.0040*
t-stat	2.47	4.91	1.70	3.52	1.67
N	105	142	142	150	140
C. Difference-in-difference:					
Diff. Post - Pre (A - B)	0.2060	-0.0153	-0.0122	-0.0008	-0.0019
t-stat	0.31	0.40	0.91	0.20	0.76

Negative rating outlook and the following resolution of Microsoft by Moody's on a timeline

July 25, 2016: **negative OL**

Dec. 7, 2017: **affirmation**

Negative outlook reflects Moody's concern over Microsoft's further increase in its gross and net leverage after Linkedin's acquisition.

<u>Major Conditions for possible subsequent rating actions:</u>
A **downgrade** if: the company's gross leverage continues to rise without a substantial increase in cash balances.

A stable outlook and rating affirmation if: there is no further increase in gross and net leverage.

Moody's **affirmed** Microsoft's Aaa rating without downgrade and changed its outlook from negative to stable. The rating affirmation reflects Microsoft's continued profitability growth and strong liquidity.

Figure 1: Negative rating outlook and the following resolution of Microsoft by Moody's

Figure 1 illustrates the negative rating outlook assigned to Microsoft and the following resolution by Moody's on the timeline (Moody's, 2016; Moody's 2017).It shows the rating actions assigned to Microsoft by Moody's along with the rationale behind its actions. On July 25, 2016, Moody's changed the outlook of Microsoft to "negative" and confirmed its Aaa senior unsecured rating. On December 7, 2017, Moody's affirmed the Aaa rating without downgrade and changed its outlook from negative to stable. The rationale behind Moody's assignments of negative outlook and subsequent resolution is given below the rating dates. Moody's also states the major conditions related to rating downgrade and rating affirmation with outlook change (from negative to stable) in the initial negative outlook report. We summarize these major conditions in the box below the negative outlook date (see Conditions for major possible subsequent rating actions).

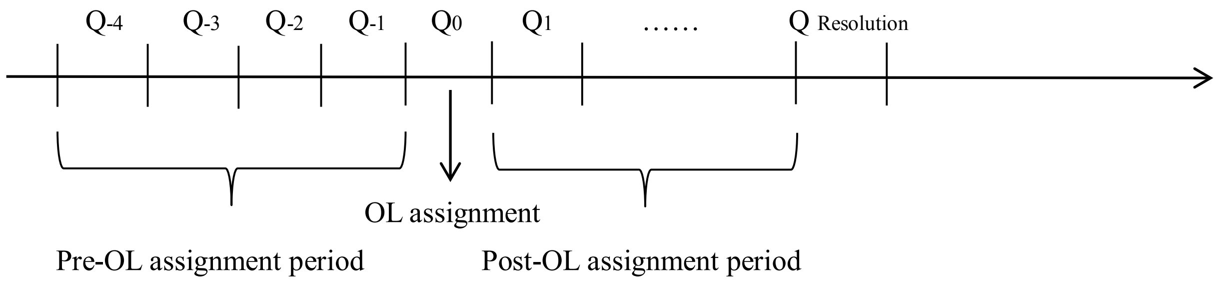
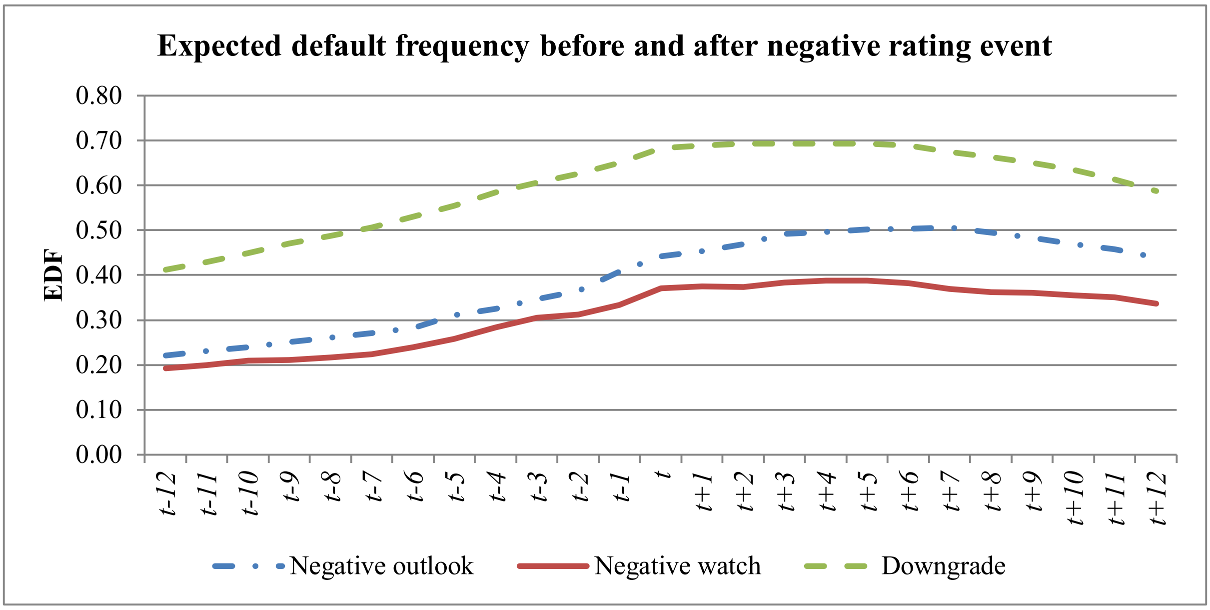
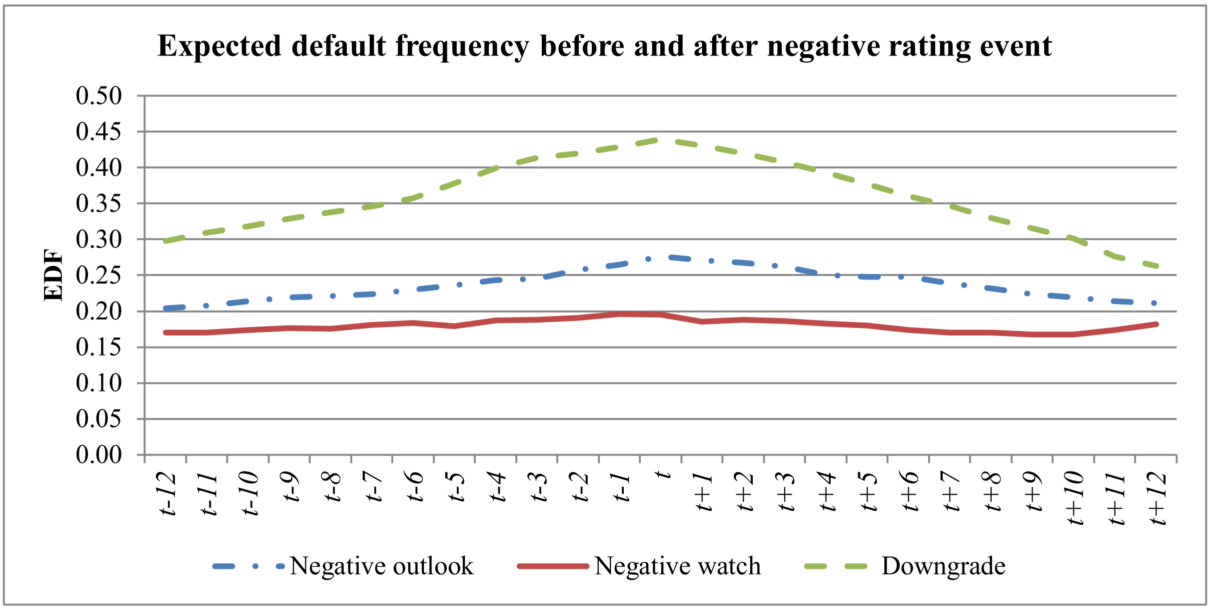


Figure 2: The time frame of negative outlook process

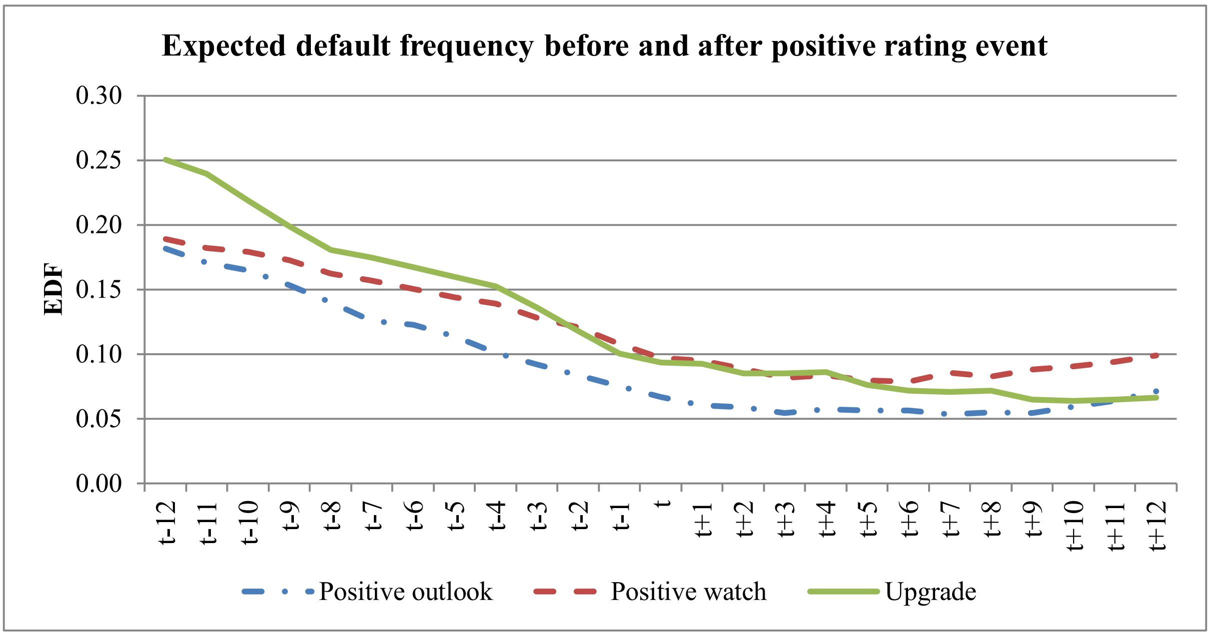


Panel A: negative rating events with subsequent downgrade

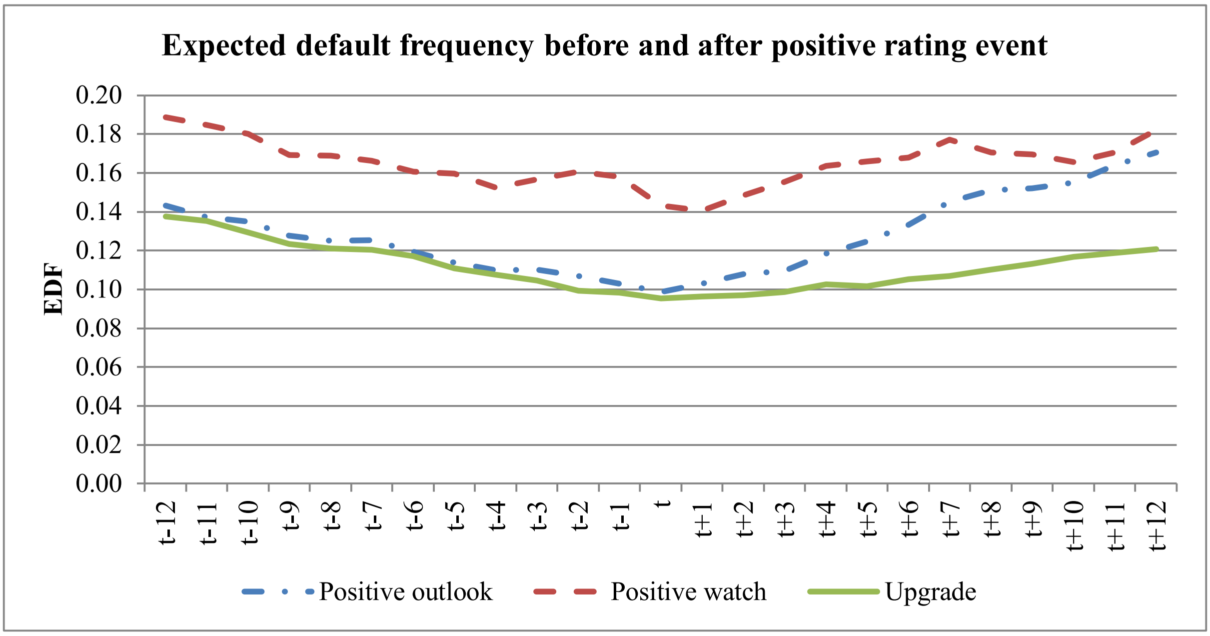


Panel B: negative rating events without subsequent downgrade

Figure 3: Default risk surrounding negative rating event



Panel A: positive rating events with subsequent upgrade



Panel B: positive rating events without subsequent upgrade

Figure 4: Default risk surrounding positive rating event

Appendix 1: Variable definitions

Variable code	Variable name and brief explanation
CAR	Cumulative abnormal return over 3-day event window
BHAR	Buy-and-hold abnormal return over 3-day event window
EDF	Expected default frequency in a month of a firm, calculated from Merton's model
ΔEDF	Change of EDF from previous month to current month of a firm
CONFIRM	Dummy variable; it equals to 1 if a firm received rating confirmation after negative OL assignment.
DOWNGRADE	Dummy variable; it equals to 1 if a firm was downgraded in the month.
UPGRADE	Dummy variable; it equals to 1 if a firm was upgraded in the month.
NEGOL	Dummy variable; it equals to 1 if a firm was placed on negative OL list in the month.
POSOL	Dummy variable; it equals to 1 if a firm was placed on positive OL list in the month.
NEGCW	Dummy variable; it equals to 1 if a firm was placed on negative CW list in the month.
POSCW	Dummy variable; it equals to 1 if a firm was placed on positive CW list in the month.
RATING	Numerical value of credit rating at the end of the month or quarter
INVESTGRADE	Dummy variable; it equals to 1 if a firm's rating is above BB+.
INTCOV	Interest coverage in a quarter; = EBITDA / interest expense
LEV	Leverage ratio in a quarter; = total debt / total assets
STDTTD	Short-term debt to total debt ratio in a quarter; = short-term debt / total debt
ROA	Return on assets in a quarter; = net income / total assets
CAPEX	Capital expense in a quarter; = capital expenditures / total assets
RECOVERY	A set of recovery effort variables including ΔINTCOV, ΔLEV, ΔSTDTTD, ΔROA and ΔCAPEX.
DINTCOV	Recovery effort variable; it is the increase of average interest coverage from pre-OL to post-OL assignment period.
DLEV	Recovery effort variable; it is the decrease of average leverage from pre-OL to post-OL assignment period.
DSTDTTD	Recovery effort variable; it is the decrease of average short-term debt to total debt from pre-OL to post-OL assignment period.
DROA	Recovery effort variable; it is the increase of average ROA from pre-OL to post-OL assignment period.
DCAPEX	Recovery effort variable; it is the decrease of average capital expenditure from pre-OL to post-OL assignment period.
OPROFIT	Operating profitability in a quarter; = operating income before depreciation / total assets
MTB	Market to book ratio in a quarter; = market value of assets / total book value of assets; market value of assets is the sum of market equity and total debt
TANG	Tangibility in a quarter; = net property, plant, and equipment / total assets
SALES	The natural logarithm of sales in a quarter
SIZE	The natural logarithm of total assets in a quarter
CASH	Cash ratio in a quarter; = cash and marketable securities / total assets
LEVGVOL	Volatility of leverage during the past eight quarters
OPROFITVOL	Volatility of operating profitability during the past eight quarters

Appendix 2

Standard & Poor's long-term issuer credit ratings and their assigned numeric values

According to S&P's, "An S&P Global Ratings issuer credit rating is a forward-looking opinion about an obligor's overall creditworthiness. This opinion focuses on the obligor's capacity and willingness to meet its financial commitments as they come due." (S&P's FS, 2017, p.6-7).

Ordinal /numeric value assigned to each rating category	**S&P's long-term issuer credit ratings**	
22	AAA	**Investment grade**
21	AA+	
20	AA	
19	AA-	
18	A+	
17	A	
16	A-	
15	BBB+	
14	BBB	
13	BBB-	
12	BB+	**Speculative grade or non-investment grade**
11	BB	
10	BB-	
9	B+	
8	B	
7	B-	
6	CCC+	
5	CCC	
4	CCC-	
3	CC	
2	SD	
1	D	