Slow ratings

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Abstract

Rating agencies came under heavy scrutiny following the financial crisis for being slow in updating the oustanding ratings making information in ratings stale. In this paper, we show that rating agencies were fully informed about the changes in the credit quality of the issuers yet chose to delay the update of outstanding ratings. First we show that equity analysts anticipate changes in ratings up to 6 months before the actual rating action. Secondly, we show that the same anticipation is found in ratings privately distributed at a cost by Moody's to private investors (Moody's Implied Ratings). These results show that ratings do not convey fundamental information while still serving as credit quality certification devices that drive the asset allocation of regulation-constrained investors. In order to minimize shocks in constrained investors portfolios, rating agencies delay the release of updates to allow reallocations before actual revisions. The role of rating agencies is therefore revised from information providers to coordination mechanisms.

Introduction

The recent financial crisis has increased the perception that rating agencies do not timely adjust ratings in response to new information on the credit quality of a company. Rating agencies have generally reckoned this problem but also stressed that the need for stability in ratings justifies a slower adjustment pace. However, recent spectacular failures in capturing obvious deteriorations in the credit quality of issuers cast doubts on the validity of this explanation.[1] In this paper we argue that equity and debt analysts process the same information but release it with very different timing. Equity and debt values are function of the same assets, however, since operating cash flows generated by those assets - both current and expected - are devoted first to debt repayment and then to equity, an improvement or deterioration in operating cash flows quickly affects equity prices while debt value changes only in response to large enough and persistent structural modification in operating cash flows. This implies that if new information generates sufficiently large swings in equity value forecasts then also debt analysts should adjust their forecasts. An efficient market for ratings would require such an adjustment to occur very close to equity value changes if the new information is truly relevant to debtholders. Alternatively debt analysts following a through-the-cycle approach should leave valuations unchanged signalling that there is still a sufficient cash-flow cushion shielding debt securities value. Previous work by Goh and Ederington (1998) found mixed evidence on the anticipation effect of equity analysts measuring equity forecasts through EPS and EPS revisions. As a measure of equity forecasts in this paper we introduce equity target prices. A target price is the stock price predicted by an equity analyst on a specific time frame, generally 12 months. Target prices are released by analysts as summary information to comprehensive equity research reports issued by research firms alongside qualitative recommendations and earnings forecasts. Differently from ratings, equity analysts firms coverage through target prices is substantially larger in depth and width as the average annual coverage per company is 46 equity forecasts issued by 9.1 research firms per year as opposed to an average of 1.4 rating actions by a maximum of three rating agencies. Womack (1996), Brav et al. (2001), Bradshaw (2002), Asquith et al. (2005), Bradshaw and Brown (2006), Bonini et al. (2010), Da and Schaumberg (2011) have investigated the quality and accuracy of target prices showing that target prices (TP) are more comprehensive and informative

[1] Notable examples are the unchanged high quality ratings still assigned to Enron (2001), Worldcom (2002), Bear Sterns and Lehman (2008) at the time of their bankruptcy filings or bailouts.

than earnings forecasts as they incorporate also estimations of future discount rates, market momentum, liquidity and firm's characteristics.

Testing our conjecture on a large, cross-country sample of 2,286 rating actions and 75,689 equity target prices we show that debt rating changes are consistently anticipated by sharp changes in the average equity price forecast for one company up to 120 days before the rating action. For equity prices forecast changes of more than 20%, the logistic likelihood of observing a one notch change in the rating in the following 120 days is above 80%. This anticipation effect is observed for both upgrades and downgrades, is stronger for financials than for industrial companies as suggested by Schweitzer et al. (1992) and Gropp and Richards (2001), and is robust to industry and country effects. Controlling our results for reverse causality, differently from Goh and Ederington (1998), we observe small and economically insignificant effects of rating changes on forward equity forecasts changes, suggesting that the release of a rating action doesn't provide new information to equity analysts. Interestingly, quasi-rating actions such as watchlist inclusions and outlook changes are largely accounted for as proper rating actions as the equity forecasts anticipation effect is stronger and more significant for the release of these ancillary valuations than for the subsequent proper rating changes.

Rating agencies delays might have been determined by a lack of knowledge of the information processed by equity analysts. Looking at a novel database of ratings privately sold by Moody's to institutional clients (Moody's Implied Ratings) we show that the evolution of private ratings closely map that of equity forecasts in anticipating rating changes. Our results provide novel evidence on the information disclosure of debt and equity analysts extending the evidence in Mansi et al. (2011) and showing that both rating providers have access to the same set of publicly available information but that they process it with very different timing. Relatedly, this result leads to the rejection of of the through-the-cycle explanation of the relative slowness of rating agencies in adjusting their valuations.

This evidence suggests that rating agencies are not information providers as the information in ratings is stale and available to the public. Differently, we believe that rating agencies act as as coordination mechanisms in a similar spirit to the one proposed in Boot et al. (2006). There is ample evidence that a large fraction of institutional investors face ratings-related constraints in their asset allocation strategies (Cantor and Packer, 1997 among others). If rating agencies released information in a timely fashion, security prices affected by the revision would adjust sharply causing a significant effect on the value of assets of investors in particular of constrained ones who would be forced to realign their portfolio to their regulation constraints. However, it's been often considered puzzling that price effects of rating changes are essentially non existing around the rating action, suggesting that the market discounts the information that leads to a revision well ahead of the rating change. We argue that this absence of price effects is due to anticipated reallocations by constrained and unconstrained institutional investors driven by public information available to investors and agencies before the rating revision. Ratings therefore still serve as credit quality certification measures but rating agencies updates are timed in a way to reduce disruption in investors portfolios due to the binding constraints in assets selection.

1 Literature Review

The timing of the release of ratings has been addressed by a few papers exploring whether the information that eventually leads to a rating action is already discounted for by market participants. Hand et al. (1992) examine daily bond and stock excess returns around rating agencies' announcements. While they do not explicitly separate the change in security prices before the rating event from that on and after it, they show a weak evidence of some bond and stock price abnormal change before a rating revision. This separation is performed by Goh and Ederington (1998) who show that while rating changes and revisions to analysts' earnings forecasts apparently bring new information to the market, there is also evidence that both react to public information that is already available. Comparing the timing of the release of rating actions and earnings forecasts, they Granger-test the causality flow, i.e. whether rating changes help predict earning forecasts, or vice versa. Their evidence suggests that most bond downgrades are anticipated by declines in earning forecasts, but EPS revisions are negative and statistically significant also up to 12 months after the downgrade. Ratings are measures of the risk of a company and therefore should be highly correlated with the most widespread market measure of risk, i.e., credit default swaps (CDS). Hull et al. (2004), Norden and Weber (2004) and Daniels and Jensen (2005) look at the effects of rating actions on CDS spreads, finding that CDS spreads rise before a negative rating action but that the change is more limited for positive rating actions. Yet in both studies, the CDS anticipation effect is statistically significant only for negative changes that are very close to the rating action announcement. Di Cesare (2006) restricts the analysis to the rating actions anticipation content in CDS spreads for large cap banks in Europe and USA. The author finds that CDS spreads, bond spreads and stock prices show significant abnormal changes before the announcements of both negative rating reviews and actual downgrades. Results for positive rating events are weaker and, consistent with previous studies, limited to a short window around the rating action.

Altman and Rjken (2004) and Cantor and Mann (2003) address the lack of timeliness by rating agencies in adjusting their valuations arguing that since ratings' informational content is long-term, valuations are changed only in response to enduring changes in cash flow. Additionally, agencies are cautious in changing ratings, as this may further weaken companies that are undergoing temporary difficulties, thereby increasing the chance of a default. Following this conjecture, debt and equity analysts whose research reports are less likely to be as impactful on firms stability, should be more informative information providers. Beaver (2006) examine the relative timeliness of reports published by EJR a non-certified rating agency, finding that they are more timely than those released by Moody's. In a side test they also show that stock market prices anticipate more EJR rating events than Moody's rating changes in the 30 days window before the event. In particular, equity prices do change in anticipation to Moody's upgrades and weakly decrease before downgrades while the reaction is more symmetric and significant for EJR events thus suggesting that non-certified agencies and equity markets seem to have a similar information revelation function. These results are similar to those obtained by Cornaggia and Cornaggia (2013) on ratings released by Rapid Ratings, a private rating provider.

De Franco et al (2009) examine the effectiveness of bond analysts as information providers in the U.S. corporate bond market. They document that sell-side bond analysts report do have an effect on bond trading volumes. Given this evidence they investigate whether bond reports lead rating events. They show weak evidence of marginal changes in the bond recommendation distribution just in the 30 days period before the rating event. Their result suggest that the sell-side bond rating analysts and rating agencies timing in releasing information to the market is substantially aligned. A similar evidence is provided by Johnston et al. (2009) who show that in the 30 days prior to a rating change equity prices exhibit a small negative abnormal returns for downgrades and positive returns for upgrades. However, the evidence is not statistically significant for upgrades and doesn't solve the causality issue for downgrades as the drag in equity prices in the 30 days after the rating downgrade is negative and significant

Finally, Womack (1996), Brav et al. (2001), Bradshaw (2002), among others have shown how sell-side equity analysts' qualitative recommendations can constitute important price-sensitive information. Barber et al. (2001), Asquith et al. (2005), Bradshaw and Brown (2006), and Bonini et al. (2010) investigate the quality and accuracy of target prices. Target prices are explicit quantitative predictions released by the analyst as ancillary summary information to comprehensive equity research reports issued by research firms alongside recommendations. Differently form EPS, target prices are comprehensive measures of the fair value of a company adjusted by exogenous factors such as market momentum, liquidity or industry factors limitedly affected by fiscal policies and strategic issues. They report that markets therefore react to TP releases and TP revisions. This evidence suggests that TPs should provide timely and, on average, accurate information, since equity research firms also compete for clients on the basis of their research quality (Strauss and Zhu, 2004).

2 Equity and debt forecasts

Assume a firm with a simple capital structure of equity and a single class of debt. At any time, the liabilities side of the balance sheet must be equal to the assets side at market values. Differently from equity, debt has a binding maturity that gives equity value a call-option-like payoff structure conditional on fluctuations in the assets value, as demonstrated by Merton (1974) in his seminal contribution. When the market value of assets fluctuates, so does the equity price due to its option-like value function. However, since debt value can be obtained by subtracting equity value from assets value, sufficiently large swings in expected assets value may affect the repayment probability of debt at maturity. This simple model implies that equity prices are by construction more volatile and that debt values can be obtained by difference. In this respect, expected changes in assets prices trigger rapid adjustments in expected equity prices but if the swing in forecasted assets value is large enough, than also forecasted debt values should change accordingly, due to ratings being essentially an estimate of the default probability which is by construction zero if the firm has enough assets to pay-off its obligations. An empirical test of this intuition relies primarily on the identification of an appropriate measure of expected equity prices as a proxy for changes in expected assets value. Goh and Ederington (1998) looked at EPS with unsatisfactory results as they found weak anticipation effects and couldn't resolve the causality relationship between information conveyed by rating events and by EPS forecasts. Hand et al. (1992) and Gropp and Richards (2001) find little relationship between equity and debt prices. We propose adopting equity target prices, i.e. explicit forecasts of expected stock prices. This measure is more comprehensive than EPS as it measures directly a firm's assets value, incorporates estimates of the future discount rate and the market momentum and is released frequently by a large number of analysts, thus providing a sufficiently accurate sampling of the assessment of experienced market participants of new information on the assets value. Additionally, equity price forecasts do causally influence stock market prices but their influence is distributed over a fairly long time frame (Brav and Lehavy, 2003) and difficult to distinguish from noise on shorter windows (Loh and Stulz, 2011). Loh and Stulz (2011) support this view, showing that only information by influential analysts generate immediate stock market reactions while the average forecast is incorporated smoothly into market prices.

Prices and forecasts are affected by the nature of the information on a company. Kasznik and Lev (1995), Skinner (1994, 1997), Baginski et al. (2002]) document that managers have incentives in releasing bad news in a timely fashion to reduce litigation costs or, as shown by Yermack (1997) and Aboody and Kasznik (2000), to lower the exercise price of to-be assigned stock options. However, managers face career concerns that may motivate them to withhold information as proposed by Hermalin and Weisbach (2007) and surveyed by Verrecchia (2001). Similarly, managers may be willing to retain bad news in the hope that foreseeable good news will eliminate the need for bad news revelation or substantially reduce their impact (Graham et al. 2005, Bonini and Boraschi, 2011).Kothari et al. (2009) provide robust evidence that bad news disclosure is delayed and that market reaction is significantly stronger for bad news announcements. This equity price adjustment implies a likely need for revising also price forecasts. Since analysts' behavior is known to be overly optimistic, i.e., they tend to overestimate (underestimate) increases (reductions) in the prices (Bradshaw, 2001; Bonini et al. 2010), large adjustments can be expected for particularly severe bad news disclosure. Therefore if an anticipation effect is observed, it is likely to be stronger for downgrades than for upgrades.

Several papers (Boot et al. 2006; Hand et al., 1992) have argued that additions or changes to the credit watchlist are used by rating agencies as "early warning" signals to the issuer. Companies are added to the credit watchlist if the rating agency believes that a rating change is likely. This information is supplemented by the direction of the expected change; e.g., there may be indicated upgrades, indicated downgrades or a developing situation. The credit watch would be a "developing situation" if a rating change of unknown direction were likely. Holthausen and Leftwich (1986) and Boot et al. (2006) show that a watchlist addition with negative valuation is followed by a negative stock market reaction. In addition, Hull et al. (2004) show that while watchlist additions trigger significant market reactions, the eventual rating actions doesn't affect market prices, suggesting that the market consider watchlists as the 'true' credit event. In this paper, we follow Hand et al. (1992) and use credit watches in two ways. As in Hand et al. (1992), we argue that a rating change that is preceded by a rating watchlist action in the same direction, delivers a significantly lower information content because the watchlist inclusion acts as the *de facto* rating action. As such, contaminated rating actions are already largely accounted for the market and, as shown by. Boot et al. (2006), cause a moderate market response. This intuition is further supported by the large correlation between watchlist inclusion and forward rating change documented in Hamilton (2004), Hirsch and Krahnen (2007) and Bannier and Hirsch (2010).

3 Sample Selection and Data

Our analysis concentrates on long term issuer ratings, which are the agencies' opinion on an obligor's overall ability to repay its financial obligations. We use distinct information from the three main rating agencies to avoid any cross-agency contamination. We collect information on all rated companies included in the large cap indices of the United States, UK, Germany, France and Italy.[2] We choose to focus on large cap companies as our tests require corporate level credit ratings and deep analyst coverage. This joint requirement would not be generally satisfied for smaller companies and this could lead to a significant sample bias. Admittedly, focusing on larger companies skew the sample towards investment grade firms. We believed that this trade-off was better dealt with by focusing on a stricter sample of large firms but avoiding any subjective imposition of cut-off points on the acceptable number of reports or rating agency coverage. We obtain data on companies in the sample as follows: we collected ratings combining information provided by Bloomberg and Datastream databases with data available directly from the rating agencies. Target prices are collected from I/B/E/S. For each firm, we exclude observations for which only one equity report has been published between two consecutive rating actions. The resulting database includes 165 continuously rated, listed companies, 2,286 rating actions and 75,689 target prices issued by 541 equity analysts over the period 1/1/2000-12/31/2009. Table 1 reports descriptive statistics

[2] The indices are: S&P 100, FTSE 100, DAX 30, CAC 40 and FTSE/MIB 40, respectively.

for the sample.

INSERT TABLE 1 HERE

Panel A reports descriptive statistics for the whole sample. Column 1 reports the number of companies for which we obtained rating actions; columns 2 and 3 show the number of target prices and equity analysts covering the company; column 4 reports the number of rating actions. Columns 5 and 6 report the average yearly number of target prices and rating actions issued for a single company, while columns 7 and 8 provide an industry breakdown. For each company, we observe an average of 1.4 rating actions and 45.9 target prices per sample year. While within-Europe evidence is largely aligned, we observe large regional differences. In the US all companies in the index are rated as opposed to Europe. The equity coverage ratio is higher in the US with over 55 TPs per company released each year vs an average of 32 for continental companies. Differently European firms are more subject to revisions by rating agencies as the average number of rating actions in Europe is approximately 2 as opposed to 1.1 for US companies. Industry distribution is homogeneous across the sample, with a ratio of industrial to financial companies slightly above 2. Italy is a notable exception, with 18 companies classified as financial and only 5 companies as industrial. This difference is in line with the composition of the Italian stock-market, which features a smaller number of listed companies of comparatively larger capitalization and mostly within the banking industry. In Panel B, we present rating actions data sorted by the country of origin of the debt issuer, rating agency and industry. The observations corresponding to an outlook removal are classified either as an upgrade or as a downgrade conditional on whether the previous outlook is negative or positive. Overall, the dataset contains 371 pure upgrades and 626 pure downgrades., 633 outlooks and 656 watchlist inclusions with either positive or negative view. Rating agencies distribution is aligned with the observed market share with S&P dominating the sample with 43% of the observations followed by Moody's and Fitch, which respectively represent 35% and 22% of the dataset. We classified rating actions according to whether they were anticipated by their inclusion in the watchlist in the same direction. The observations corresponding to outlook removal not followed by a rating action are classified either as an upgrade or as a downgrade, conditional on whether the direction of the previous outlook. For instance the removal of a negative outlook is coded as a positive event.

4 Methodology

Rating changes include upgrades and downgrades, as well as positive and negative outlooks, and watchlist addition or removal. Following the different rating structures adopted by the three main rating agencies, we transform nominal ratings into a numeric format with 1 representing the highest rating (e.g. AAA in the S&P scale) and higher integers for lower quality ratings. For instance a BB rating would be codified as 13 as S&P reports 12 higher rating assessments. Accordingly, a one-notch change is expressed by a one-integer decrease for downgrades and a one-integer increase for upgrades.

We identify a rating action (RA) as the difference between two consecutive rating events (R) and we compute it as:

$$RA = (R_t) - (R_{t-1})$$

The outcome of this metric is a single or multiple "notch" changes in the company rating, where a notch is defined as any one-step movement in the rating. For instance a movement from $Ba1$ to $Ba2$ represents a single notch downgrade, whereas a movement from $Ba1$ to $Baa2$ represents a two notch upgrade.[3] A non-trivial methodological issue is the treatment of quasi-rating actions such as outlooks or watchlist inclusion. In our dataset, we record upgrades and downgrades both in isolation and accompanied by outlooks or revisions. As such we develop three different measurement of $RA:$ the first all-encompassing methodology classifies as a RA all non-overlapping actions, i.e. pure upgrades and downgrades, watchlists and outlooks issued in isolation. This approach follows the intuition in Boot et al. (2006) that rating agencies use weaker statements such as outlooks or watchlist to 'warn' the firm and the market before an actual rating event. These quasi-ratings have no or marginal impact on several relevant issues such as contractual interest rates conditions or covenants, allowing the firm and the investors to take appropriate actions. However, due to the strong evidence documented in Keenan et al. (1998), Hamilton (2004) and Hirsch and Krahnen (2007) that the vast majority of watchlist eventually translates into actual rating actions, the market response to these events is close to that of a rating action suggesting that it can be appropriate to consider any statement as a credit event. In the second approach we take into account the evidence that ratings may be issued alongside additional statements (e.g. one notch downgrade and a negative watchlist inclusion). Accordingly we classify rating actions into single and multiple RA conditional on whether the upgrade or downgrade is issued

[3] The example adopts the Moody's ratings scale.

in isolation or is accompanied by further assessments. In such a case RA assumes values equal to the upgrade or downgrade action but is coded as a 'multiple' rating action; finally we control for actions anticipated by watchlist inclusion or outlooks issued by the same agency thus identifying uncontaminated and contaminated groups as in Hand et al. (1992). In our analyses we adopt the first methodology as the reference and run separate tests for controlling the differential impact of different behavior by rating agencies.

In table 2 we report summary statistics on RA following the first approach.

INSERT TABLE 2 HERE

The average rating across the sample period fluctuates from a highest rating of 9.16 in 2007, corresponding approximately to a BBB+ level in the S&P scale to a lowest average of BB+ or 12.09 in 2004. RA assumes values ranging from -5 to +4, however, multiple notch changes are uncommon as 89.97% of the rating changes in the sample fall in the $\{-1, 0, +1\}$ range. The mean and median time between a watchlist inclusion and its resolution through a removal or a rating change are 96 and 76 respectively, in line with results in Hull et al. (2004) Hirsch and Krahnen (2007) and Bannier and Hirsch (2010). Target prices fluctuate significantly from a minimum of 40.98 to a maximum of 106.38, in line with the observed evolution of global stock markets during the period of analysis and consistently with the predictions obtained through the simplified Merton approach presented above.

Conditional on the realization of RA, we calculate the Change in Target Prices (CTP) prior to each rating action across three different observation windows $T = [-60; 0], [-90; 0], [-120; 0]$ with daily observations. We concentrate our analysis on these intervals considering that 1) for shorter windows (i.e., <60 days) the frequency of TP changes become negligible and that 2) for larger windows (i.e., $>$ 120 days) results may be misleading since CTP windows for different rating actions may overlap preventing to draw meaningful inferences. To allow causality controls, we also compute CTP values for three forward lags following the rating action: $[0; +60]$; $[0; +90]$; $[0, +120]$.

For each selected window we compute the CTP_i for each company i as follows:

$$CTP_i(T) = \frac{\sum_{j=1}^{J} \sum_{n=1}^{N} \frac{\left(TP_{n|j} - TP_{(n-1)|j}\right)}{TP_{(n-1)|j}}}{M} \forall \ RA$$

where:

T is the selected observation window as previously specified

$j = \{1, ..., J\}$ is the target price issuing analyst;

$n = \{1, ..., N\}$ is the ordinal number of reports issued by analyst j on company i within the observation window, with 1 indicating the oldest report;

$(TP_{n|j} - TP_{n-1|j})$ indicates the difference between two contiguous target prices issued by the same analyst j;

M is the total number of TP changes for all analysts recorded for each company i within the relevant observation window T;

RA is the rating action .

Note that we calculate the TP change as $(TP_{n|j} - TP_{n-1|j})$. Since the first TP issued within the observation window is $n = 1$, then $TP_{n-1|j}$ will be out of the observation window. This approach may lead to including TP changes that have originated upon information released before the observation window. However, in unreported tests controlling for the alternative option of adopting $(TP_{n+1|j} - TP_{n|j})$, we observe a significant reduction in the number of observations - especially for smaller windows - together with a decrease of the statistical significance and no significant changes in results. Figure A1 in Appendix reports a plotting of RA and TP over the sample period, showing hints of faster adjustments in the equity market.

Once $CTPs$ have been estimated for all i we calculate the *Average Change in Target Price* $(ACTP)$ as follows:

$$ACTP\,(T) = \frac{\sum_{i=1}^{I} CTPi}{I} \mid RA$$

Table 3 reports average $ACTP$ values by rating action.

INSERT TABLE 3 HERE

The average change in target prices before the credit event seems to be correlated in sign and size with the corresponding rating action. $ACTP$ is largely negative for downgrades, ranging from -40% to -8% conditional on the severity of the downgrade and the $ACTP$ computation period; similarly $ACTP$ is positive in the 60, 90 or 120 days prior a positive rating action, with a range from +4% to 17%. Interestingly, there is no clear pattern of the $ACTP$ metric in any of the computation periods following a rating action, independently from the notch change and we also observe some unexpected results like positive changes for very large negative credit event. The mapping of this summary statistics is reported in Figure 1 and intuitively suggest a nexus of causality between changes in equity forecasts and ratings aligned with our intuition.

INSERT FIGURE 1 HERE

5 Results

We begin addressing more formally this intuitive evidence by running a set of linear regressions of rating changes on the three different measures of prior changes in target prices and of changes in equity forecasts conditional on changes in ratings as a control. Results reported in Table 4 provide an initial support to our first hypothesis: the first three models show that a one notch change in rating is associated with prior changes in CTP in excess of 20%. This result is fascinating as the target price change associated with a one-notch rating change falls at 20%, a level associated with a stock recommendation class transition as observed by Brav and Lehavy (2003). In particular, Brav and Lehavy noted that a stock recommendation revision from a 'hold' class to a Strong Buy or Strong Sell class is associated with changes in target prices of 22.8% and 20.6% respectively.

INSERT TABLE 4 HERE

The long term model is slightly stronger in size and significance suggesting that the information leading to a rating event is incorporated in equity revisions well in advance. R^2 and F-tests suggest that these conclusions have a meaningful economic significance. Models 4 to 6 regress the changes in equity forecasts following a rating action to investigate whether there is some valuable information released by debt analysts that affects also expected equity values. Our results do not support this view. Models significance is very low with R^2 below 3%. Estimated parameters are significant but very small indicating that equity forecasts may experience some residual drag in their adjustment but not a significant change in response to the rating action. In fact, in order to observe a 20% change in target prices ratings should change by almost 7 notches, a level of revision that is absent from our dataset and almost never observed in financial markets

We now investigate this preliminary support to our main intuition by adopting a multinomial logistic data regression approach to estimate the probability that a given rating action actually occurs, given a change in the independent variable.

In particular, we estimate the following model:

$$\Pr\{y_i = j\} = \frac{\exp\left(X_i \beta_j\right)}{1 + \sum_{j=1}^{J} \exp\left(X_i \beta_j\right)}$$

where for the ith observation, y_i is the observed outcome for $j \in RA$ and X_i is the vector of explanatory and control variables. Whenever possible we adopt the "confirmed rating" (rating action=0) as the baseline group to allow easier results interpretation.

Table 5 shows the estimated likelihood parameters associated with each rating actions using different windows of changes in target prices (CTP) as the explanatory variable.

INSERT TABLE 5 HERE

The sign of the parameters confirms our first hypothesis and is negative for downward revisions and positive for upward ones. This indicates that positive and negative rating actions are anticipated by changes in the outstanding equity forecasts in the same directions. Confirming the intuitive evidence in figure 1, parameters' signs increase for larger rating actions indicating that extreme credit events (e.g. 5 notches downgrades) follow larger changes in target price revisions. Interestingly, the models and parameters significance increases for larger estimation windows. This result is noteworthy in that it signals that equity markets incorporate new information that is debt-relevant well before the actual rating action. As outlined in hypothesis 2, the anticipation effect is stronger in size for negative credit events. From an economic perspective our parameters are surprisingly large as the probabilistic transformation applied to the 120 days model suggests that a one hundred basis point increase in the target price change is associated with an increase of 4% in the likelihood of observing a rating event. Recalling the previous evidence on the 20% target price threshold, this implies that for 20% changes in equity forecasts the likelihood of observing a rating event after 120 days is a whopping

80.2%. The mapping of the estimated probabilities for -1, 0 (the baseline), and +1 notch rating in Figure 2 provides comforting support; the baseline case is appropriately bell-shaped around a zero target price change indicating that an unchanged rating is anticipated by stable equity forecasts and that it is extremely unlikely to observe an unchanged rating following a large change in target prices.

INSERT FIGURE 2 HERE

Inspection of Figure 3 reporting the distribution of equity forecasts changes for the baseline case supports this view and show that essentially no observations are recorded beyond the +/- 20% equity price forecast change threshold.

INSERT FIGURE 3 HERE

Additionally, the Kernel density function plot is narrower than the normal distribution function indicating a higher concentration of observations around the zero change value.

All models are strongly significant with $pseudo - R^2$ of 7.6% to almost 10%, and, more importantly, χ^2 values ranging from 294.57 to 382.84. However, standard errors are increasing in the magnitude of the rating action and, consequently, significance decreases, suggesting that the model fit deteriorates for these events. We attribute this evidence to the narrowing sample size for extreme observations. Therefore, in the following tests we will restrict our analysis to the {-1,0,1} subset of rating changes and to the 120 days window that shows the highest statistical significance.

5.1 Industry and Credit Rating Agency test

In Table 6 we report a set of multinomial logistic regressions on the restricted sample introducing a vector of controls. In the first model we run the analysis controlling for country, rating agency, industry, year and investment grade effects.

INSERT TABLE 6 HERE

Parameters estimates are essentially unchanged in size and significance supporting previous results while model quality increases sharply. Both positive and negative rating changes are anticipated by appropriate changes in equity forecasts. The control dummy parameter (unreported) is insignificant indicating that the anticipation effect of equity forecasts is not affected by the initial quality of the rating as measured by the investment/speculative grade dummy variables. This is a little unexpected as rating events that could possibly change the rating class quality, for example from investment grade to speculative or vice versa, might be associated with larger effect. However, given that it is extremely unlikely to observe multiple-notch changes, this effect should be observed mainly for firms' ratings lying very close to the rating grade transition area. In all other cases, rating changes that do not affect the rating grade class do not have additional informative value. This interpretation is consistent with evidence in Cheng and Subramanyan (2008) who show that credit ratings are inversely related with the intensity of analysts following. The economic effect of the explanatory variable is large as moving from half a standard deviation below the mean to half a standard deviation above the mean CTP increases the probability of observing a rating action by 23%. The second part of Model 1 introduces controls for stock market price changes and the sign and magnitude of the previous rating action. Results are unaffected for downgrades while for upgrades CTP lose predictive power. Interestingly, there seem to be little autocorrelation for downgrades as the parameter is insignificant, whereas upgrades are more heavily correlated with past actions by rating agencies.

Model 2 confirms the predictions in hypothesis 4 in showing that the anticipation effect is different for financials than for industrial borrowers. Rating actions for financials are uncorrelated with stock market prices or past rating actions. On the other hand industrials are the main source of the correlation with past actions recorded on the full sample. In both subsets positive credit events are not meaningfully anticipated by positive changes in equity forecasts. The economic consistency of this result is also supported by the inverted significance of intercept and CTP estimated parameters that suggests the lack of a meaningful relationship. These results provide support to the arguments in Schweitzer et al. (1992) and Gropp and Richards (2001) that the higher regulation of the financial sector with higher disclosure standards, weakens the economic reaction to the release of most of the new information and conversely, triggers sharp adjustments in response to unexpected or particularly severe information. The recent financial crisis has provided striking examples of such a pattern and in the next section we provide some further evidence.

Turning at rating agencies results reported under Model 3, we do not find stark differences in the behavior of rating agencies that seem to be homogeneously lagging behind the change in equity forecasts. For negative actions this relationship is large and significant, while there is limited predictive power for upgrades.

5.2 Watchlist and outlook effects

Thus far, we have disregarded the information value of watchlists and outlooks. However, as argued in hypothesis 3, these quasi-ratings deliver important information to the market. In this respect, the anticipation effect of equity analysts should be observed also before watchlist inclusions and/or outlooks and, following the evidence in Hull et al. (2004), should be stronger. In table 7 we address this issue by analyzing the differential anticipation effect of equity forecasts on a more accurate definition of rating event. We begin with testing our conjecture on a restricted sample of actual rating actions issued in isolation.

INSERT TABLE 7 HERE

The general statistical quality of the model and the parameters signs are aligned with those obtained with Model 1 in the general sample tests reported in Table 6. However the parameters size for the independent variable increases suggesting that outlooks and proper ratings[4] are issued in response to slightly different information sets, and that the information leading to an outright rating event is, not surprisingly, more important. Differently, we obtain a larger anticipation effect when the credit event is articulated in more than one statement, for example a rating downgrade issued jointly with a further negative outlook. This result is not striking per se as it seems reasonable that if the company's conditions deteriorate markedly, than the rating agency response will be accordingly strong. Yet, it casts doubts on the timeliness of the rating agencies actions: in fact equity markets incorporate the same information well in advance with larger adjustments in forecasted prices. In a similar vein, it could be reasonable to expect rating agencies to 'warn' borrowers with some quasi-rating statement and then

[4] It is worth recalling that previous models adopted as RA the first approach detailed in section 4 that includes actual rating events and outlooks if the latter are issued in isolation and satisfy some conditions.

follow-up with a rating change. Differently, rating agencies seem to concentrate all the changes in one single point in time. This intuition is supported by the results in Model 3 where we run regressions on watchlists only. The parameter estimate is very large and statistically significant indicating that the information leading to the inclusion in the credit watchlist is processed by equity investors in full anticipation of a future rating action. Model 4 and 5 further tests this intuition running regressions on the subsets of contaminated and uncontaminated rating actions as previously defined following Hand et al. (1992). Remarkably, the equity forecasts anticipation effect is almost identical for uncontaminated events and watchlists supporting hypothesis 3 and consistent with Hull et all. (2004) and Hill and Faff (2007), although the latter contribution results are obtained on sovereign ratings. The parameter for contaminated events is smaller as expected but close to that of uncontaminated events. Ideally, this should not be the case as if the true rating event is the watchlist inclusion than the eventual rating action should be fully accounted for by the market. However in our sample, the median time between a watchlist and the rating event is less than 80 days, thus suggesting that using CTP computed on a 120 days window leads to substantial overlapping. We control this intuition by running a regression of contaminated rating actions on CTP measured on a 60 days window (adjusting the controls accordingly) and we obtain,as expected a drop in the size and significance of the estimation.

5.3 Firm level characteristics

Some firm-level characteristics are known to affect the value of firms assets and liabilities. High leverage impact negatively firm value as it increases the probability of default while assets tangibility increases firm value as it can act as a collateral to firm liabilities. Additionally, some industries or businesses show intrinsic higher equity volatility than other and this can affect the quality of the estimation. In table 8 we control for these factors. Control variables are computed as follows. Leverage is computed as in Baker and Wurgler (2001) as follows: book debt is defined as total assets (COMPUSTAT Annual Item 6) minus book equity given by total assets less total liabilities (Item 181) and preferred stock (Item 10) plus deferred taxes (Item 35) and convertible debt (Item 79). Book leverage is then defined as book debt to total assets. Market leverage is defined as book debt divided by the result of total assets minus book equity plus market equity defined as common shares outstanding (Item 25) times price (Item 199). Since leverage effects are likely to be non-linear and increasing in leverage we include a quadratic specification of leverage and introduce an interaction term with the main explanatory variable.

Tangibility is computed following Berger et al (1996) and Campello (2007) as:

$$Tangibility = 0.715{*}Receivables{+}0.547 * inventory + 0.535 * Capital$$

where Receivables is COMPUSTAT item #2, Inventory is item #3, and Capital is item #8. Since this is an absolute dollar value measure, to allow cross-sectional comparability we scale this measure by total book assets, as suggested by Berger et al (1996). Tangibility is obviously linked to leverage therefore we compute an interaction term between leverage and tangibility. However a large level of tangible assets can be a valuable collateral to liabilities that can reduce their sensitivity to total assets fluctuations. In such a case equity fluctuations would be less correlated with a rating event. Therefore we estimate tangibility also in interaction with CTP.

Volatility is defined as the weekly standard deviation of common equity prices in the 6 months before each rating event Volatility is included in the regressions as a stand alone variable and in interaction with leverage.

Table 8 report the results

INSERT TABLE 8 HERE

In all specifications the key right-hand side variable (Change in Target Prices in the 120 days window) is significant and unchanged in sign and size, thus supporting our conjecture that the information that leads to a rating event is largely available in markets well ahead of the actual rating event. Leverage, reduces the anticipation effect of equity analysts at a decreasing pace, as suggested by the negative sign of the squared specification, but cancels out any incremental information only for extreme leverage values. Tangibility is limitedly significant and not surprisingly, inversely related in sign with leverage measures. Finally, structural equity volatility as measured by the six months market model beta is not significant in explaining rating events, suggesting that what determines a change in credit quality is truly new information on the assets value that is captured by equity analysts in a timely fashion and eventually incorporated in a rating event.

In untabulated results we also control for two explicit default measures, Altman Z-score and Ohlson O-score, and by splitting the sample by size without finding significant results for these measures.

5.4 Financial crisis

The previous results cast serious doubts on the timeliness of the release of information by rating agencies. Unfortunately this is not a trivial market inefficiency as ratings are at the core of regulatory requirements, investment portfolios decisions and capital structure selection. Agencies in this respect have always highlighted the "opinion" feature of ratings shielding from accusation of being a potential factor in assets misallocation and markets instability. Following the recent financial crisis, both the US through section 939A of the Dodd-Frank act and the EU, have addressed the need for adopting different measures of creditworthiness to avoid over-reliance on credit agencies whose conflict of interests and dismal performance in identifying credit quality deterioration have played a significant role in the development of the crisis. However, no or very limited specific actions have been taken to date and, global markets still heavily depend on rating agencies. In this light, it is interesting to investigate the joint behavior of equity and debt forecasts during the financial crisis.

In Table 9 we report yearly regressions for the whole crisis period from 2007 to 2009 and for each of the three years. We identify 2007 as the last year of the pre-crisis boom market, 2008 as the crisis year and 2009 as the first recovery year, albeit from a financial markets perspective only.

INSERT TABLE 9 HERE

Results show that the model significance is aligned with that of the full sample but indicate some sharp yearly differences. In particular, we report a drop in significance in 2009 in particular for upgrades. The plot of the yearly average rating and CTP reported in Figure 4 helps interpreting this result.

INSERT FIGURE 4 HERE

In particular in 2008 in response to the plummeting market conditions both CTP and RA dropped. Differently, in 2009, following the recovery in stock markets that yielded an annual return of the MSCI global index of 26.8%, CTP have been upward adjusted but RA have minimally followed. Our data do not track 2010 and recent months but an improvement also in the debt market has been recorded following the recognition of lower than expected defaults in both the investment grade and high yield markets.[5] This evidence suggests the possibility that rating agencies have been too slow to revise outstanding ratings before and during the crisis and possibly may be overcautious in issuing upgrades in a situation where markets have not yet fully stabilized. If this were the case, then it would be a worrying sign of the absence of meaningful changes in the timing of the release of information by rating agencies that would further support the regulatory call for a reduced mandatory reliance on this information source. Our data are by no means conclusive in this respect but call for further accurate verification in the upcoming future.

6 Rating agencies private ratings

The previous results show that both equity and debt analysts respond to the arrival of new (significant) information on the quality of the firm. However, rating agencies fail to incorporate that information for a surprisingly long time. This behavior is hardly the effect of a "through the cycle" approach because if equity price forecasts change by a sufficiently large amount, then debt ratings will almost mechanically follow through. This evidence is robust to a large number of alternative explanation and controls and raises an important question: were rating agencies aware of this information?

In order to address this question we would need to observe the information flow within a rating agency, which is impossible. However, we believe we can obtain an acceptable proxy by looking at an additional product sold by one rating agency, Moody's, to institutional investors: Moody's Implied Ratings (MIR). MIR are daily ratings obtained by Moody's by applying a proprietary methodology to equity, debt and CDS prices. The output of this process is a rating that can be used to asses the creditworthiness of an issuer independently form the outstanding public rating and, arguably, to compare the former with the latter to identify possible misalignments.

The working hypothesis therefore is that if Moody's processed information as equity analysts did, MIR should closely map CTP in anticipating rating actions. Alternatively, if MIR are uninformative this would yield support to the idea that equity an debt analysts have fundamentally different approaches to processing information.

[5] See: Moody's Investor Service 2011, Fitch commentary 2011; Financial Times, "Junk Bonds yield hit record low", 2/18/2011.

MIR data are not public but we have obtained special access to the historical time series from 2003 (the inception) to 2012 directly from Moody's. In Table 10 we report some descriptive statistics censoring observations in 2009 for consistency with the CTP sample.

INSERT TABLE 10 HERE

We have 5,261 unique companies in our sample for a total of 16,324 rating actions. MIR are not always available for all markets or firms and that explains why the number of MIR is lower than that of the rating actions. Issuers are distributed across four macro regions (Americas, EMEA, Japan and Asia) and show an acceptable balance across macro industries.

On this sample for each MIR we compute a measure, MIR predicted change, as the difference between the outstanding rating and the relevant MIR 120 days before the actual rating action in order to replicate the approach followed for CTP. Consistent with the transformation of ratings in a numeric scale as described in section 2, this measure can be interpreted as a prediction of a downgrade if the calculated difference is negative and viceversa.

We then run a set of multinomial logistic regressions replacing CTP with MIR predicted change as the explanatory variable.

INSERT TABLE 11

The results reported in Table 11 show a surprising explanatory power of MIR predicted changes in capturing actual rating actions. The magnitude of the effect is very similar to that of CTP and the economic effect is also similarly large. Previous rating actions are correlated with actual rating changes but this doesn't affect the anticipation effect of MIR on Moody's rating actions.[6] These results strongly indicate that rating agencies and equity analysts receive and process the same information sets at about the same time. However, rating agencies selectively choose to incorporate this information in privately distributed signals well before releasing it in a publicly observed rating. This result fundamentally adds to the evidence in Cornaggia and Cornaggia (2013),

[6] In the Appendix we report a robustness test run on the subsample of Moody's MIR for which we also have CTP signals. Results are qualitatively the same.

who show that public ratings lag severely behind private ratings issued by an investor-pay agency, Rapid Ratings, by showing that rating agencies have different disclosure policies and intentionally choose to delay updates when new information on the credit quality of the issuer arrives.

6.1 False positives

A possible concern with our approach is the extent to which both MIR and CTP signals are affected by false positives. This is a common problem in financial modelling when the signal erroneously predicts an effect. A commonly adopted methodology to address this issue is running a standard Receiver Operating Characteristics analysis using a probit specification of MIR and CTP. One of the many advantages of ROC is the natural interpretation of its main output, the Area Under the Curve (AUC), as the probability that a signal correctly predicts the event.

We perform this test for both CTP and MIR and report the results in Figure 5.

INSERT FIGURE 5 HERE

ROC analysis yields results that are surprisingly close for both CTP and MIR suggesting that both predictors return a relatively low ratio of false signals. The AUCs are in excess of 75% and 70% for, respectively CTP and MIR and hold almost identically both on the observed and the estimated data.

7 Investors Trading

The previous evidence suggests that the information in ratings is stale and available to the public. Additionally, rating agencies themselves process the same publicly available information and release it privately to selected clients through alternative rating products such as Moody's Implied Ratings. While it is commonly believed that CRAs have been - and still are - prone to severe conflict of interests, plain errors or even fraud, we believe that this behavior is rational when changing the interpretation of the role of rating agencies from information providers to credit certification entities that regulators need to design appropriate rules to control the risk-taking behavior of economy-relevant investors such as pension and insurance funds or money market funds. In this view, third party credit quality assessments are needed to allow manageable monitoring of regulated investors, which would be overly difficult to achieve without an unrelated, homogeneous evaluation of the credit risk of thousands of investable securities. In this perspective, updates need not to be particularly timely. On the contrary, since a large fraction of institutional investors face ratings-related constraints in their asset allocation strategies (Cantor and Packer, 1997 among others), if rating agencies updated ratings in a timely fashion, security prices affected by the revision would adjust sharply. This abrupt price adjustment would determine a significant effect on the value of assets of investors, mainly constrained ones, because they would be forced by regulation constraints to realign their portfolio thus realizing significant losses. Rating agencies, cognizant of this, time rating updates to reduce disruption in investors portfolios due to the binding constraints in assets selection. This conjecture is consistent with the evidence, often considered puzzling, that price effects of rating changes are essentially non existing around the rating action. In our view, the absence of price effects is due to anticipated reallocations by constrained and unconstrained institutional investors driven by public information available to investors (and agencies) before the rating revision. CRAs make portfolio rebalancing limitedly impactful on constrained investors wealth by delaying updates appropriately.

This conjecture is supported by our results but can be confirmed only by looking at investors behavior around a RA. It is well known that data on bond trades with a clear identification of the trading party are essentially unavailable therefore a direct test of the implication of our conjecture is difficult to devise. However we try and provide an approximated evidence by looking at trades around a RA as captured by TRACE data. A support to our theory would be given by observing significantly different volumes of trades before and after the RA.

We collect TRACE data for all bonds affected by RA in the MIR dataset. Most of the previous studies using the TRACE database faced limitations given by the censoring of trade value at the 5 million dollars level for investment grade bonds and 1 million dollars for high yield securties. We obtained uncensored data from FINRA and use only interdealer trades to minimize the risk of including retail trades. Unfortunately TRACE doesn't provide a better identification of the counterparties of each trade and we acknowledge that our results are affected by this data limitation.

Matching the MIR dataset with TRACE yields a usable set of 5,346 rating actions and 838,941 non-retail trades. We then compute the unconditional average daily trade volume for each bond throughout its life in TRACE and compute a measure of abnormal trade volume as the percent difference of each daily volume over the unconditional mean. We then compute the cross-sectional abnormal volume before and after the rating update by rating event class. For example for a one-notch downgrade we compute the abnormal volume before and after the rating event for all bonds affected by a -1 downgrade and compute the average abnormal volume for that class. In the light of previous and existing results, we focus our analysys on downgrades only. Figure 6 illustrate the results. In the 350 days before a negative rating action we observe an average trading volume 48% higher than the historical mean trading volume indicating that large investors actively sell the securities that will be affected by the downgrade. Following the rating action the trading level drops by 40% below the mean. This level is not suggestive of a large repositioning but rather of residual trades motivated by either residual rebalances or by trading activity that is unrelated to the previous rating action which has been fully discounted in the market. The difference between trading volumes is not only large but also strongly significant. In a standard t-test we obtain $p<0.001$. Adopting a regression approach and controlling for industry, year, issuer fixed effects we confirm both qualitatively and quantitatively our results .

Clearly this result is only approximated but despite the severe data limitation we believe it's a fairly strong support to our conjecture. Future availability of better data breaking down trades by investor type will allow conducting conclusive tests.

8 Conclusions

Both bond rating agencies and equity analysts evaluate publicly traded companies, offering their opinions as a service to investors. Yet, as the recent financial crisis has clearly shown, the quality and timeliness of this information is questionable and has triggered explicit statements by US and European regulators calling for a replacement of ratings as credit risk measures for government and regulated institutions. Given the importance of assessing the quality and timeliness of this measure, a large body of academic research has investigated whether rating actions are anticipated by publicly available information such as market prices, CDS spreads or EPS forecasts without finding conclusive evidence. In this paper we follow a simple corporate finance argument and conjecture that equity price forecasts can anticipate forward rating events. Merton (1974) showed that since equity is junior to debt, it is endogenously more risky and therefore highly sensitive to changes in cash flows. This elevated intrinsic riskiness is captured by a higher volatility of equity prices due to their option-like structure and by the much larger frequency of equity research being released to the market by equity analysts. Conversely, debt is a safer security that is affected by larger swings in cash flows. Given this structure of firms' liabilities values, significant swings in expected cash flows will be quickly factored into equity forecasts. In such a case, a major change in one company expected prices may indicate a permanent change in the company's fundamentals, which is also meaningful for debt holders. Yet, while equity analyses are provided by a large number of sources and are updated rapidly, credit ratings released by the three existing agencies are apparently slower to adjust and allegedly fail to incorporate in a timely manner the new information available to the markets.

Differently from previous literature, we adopt equity target prices as a measure of stock price forecasts. Our results show that target price changes incorporate valuable information for debtholders, since most downgrades (upgrades) are anticipated by significant declines (increases) in target prices. In analyzing the change in target price as calculated over three different intervals before each rating action, we find that the sign of the estimated parameters is, as expected, negative for the downward revisions and positive for upward modifications. Results hold for any level of rating action but are statistically more significant for single-notch rating actions (-1;1) which however represent almost 90% of the sample. The anticipation value of equity forecasts is strong, significant and robust to a large number of controls. Generally downgrades are more likely to be captured by previous changes in target prices supporting the literature on deferred disclosure of bad news by corporate managers. In line with the arguments in Gropp and Richards (2001) and Schweitzer et al. (1992), we observe evidence of a significant sector effect when partitioning our sample between financial and non-financial companies. Our results show a significant difference between the two groups of issuers, mainly due to the different regulatory regimes for financial and non-financial issuers, which imply different degrees of transparency, and possibly to the different methodologies adopted to evaluate financial and non-financial firms.

Consistent with previous studies we show that watchlists are interpreted as actual rating action as the anticipation effect of outright upgrades or downgrades and of watchlists issued in isolation is essentially identical. Differently, rating revisions following a previous watchlist inclusion are less meaningfully anticipated by changes in equity forecasts because expected prices have already been corrected prior to the watchlist inclusion for the new information that eventually leads to the rating event. Since ratings are often issued jointly with additional statements such as outlooks, we control for single and multiple rating events finding strong anticipation effects in the equity market that cast doubts on the disclosure strategy of rating agencies.

Given the importance of timely rating updates for investors, it is important to understand whether this is a deliberate decision by rating agencies or rather the effect of a different approach to information processing. In order to answer this crucial question we perform a set of tests on a unique dataset of ratings sold by Moody's to private investors: Moody's Implied Ratings. MIR are estimated daily through a proprietary algorithm building on publicly available prices for equity, bond and CDS of each issuer. In this respect they are close to CTP and should track the behavior of the latter. In our tests we show a striking similarity of CTP and MIR in anticipating actual rating actions. This important result support the view that rating agencies unnecessarily delay the update of outstanding ratings. A "looking through the cycle" rival hypothesis would imply that CTP and MIR shouldn't have a sistematic and strong anticipation effect. However our evidence shows that if changes in CTP or in MIR are large enough, a rating action almost mechanically follows through. We explain this surprising evidence showing that rating agencies act as as coordination mechanisms for investors constrained by regulation such as pension and insurance funds. If ratings were updated without previous notice, prices of securities affected by the revision would adjust sharply. Constrained investors would be forced to realign their portfolio to comply with regulation limits, potentially realizing significant losses. In order to minimize this cost to investors rating agencies time the release of updates allowing investors to rebalance well-ahead of the actual rating update, as shown by consistently higher(lower) pre(post)-event trading activity by institutional investors.

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Table 1

Descriptive statistics

This table presents descriptive statistics for the whole sample in the period 1st January 2000 - 31st December 2009 with rating actions issued by S&P, Fitch and Moody's , Target Price issued by sell-side equity analysts on companies listed in the Large Cap indices of Germany, UK, France, Italy and USA. Panel A presents data on the number of Target prices, number of rating actions, number of firms, analyst coverage and the industry breakdown for the five countries included in the sample. Average # TP and Average # RA are the average number of target prices issued on one company in one year and the average number of rating action issued on the same company in one year. Panel B presents data breakdown for rating actions by Country, Agency and Issuer Type, including watchlists. Watchlist removals not followed by a rating action are counted as upgrades if the previous outlook was negative and viceversa.

PANEL A: Summary Statistics

Country	Firms	Financials	Industrials	Rating Actions	Target Prices	Analysts	Average # RA	Average # TP
Italy	23	18	5	371	4,776	67	1.6	20.8
United Kingdom	15	5	10	244	5,121	85	1.6	34.1
France	15	5	10	292	5,051	69	1.9	33.7
Germany	12	3	9	266	5,768	78	2.2	48.1
USA	100	14	86	1113	54,973	242	1.1	55.0
Total	165	45	120	2,286	75,689	541	1.4	45.9

PANEL B: Data Breakdown

BY COUNTRY									
Year	Downgrade	Upgrade	Positive Outlook	Stable Outlook	Negative Outlook	Negative watch list	Positive watch list	Total	%
Italy	60	50	61	28	76	53	43	371	16%
Germany	67	29	23	20	37	62	28	266	12%
France	68	33	29	24	46	58	34	292	13%
United Kingdom	70	28	19	16	35	46	30	244	11%
USA	361	231	3	162	54	217	85	1113	49%
Total	626	371	135	250	248	436	220	2286	100%
BY AGENCY									
Agency	Downgrade	Upgrade	Positive Outlook	Stable Outlook	Negative Outlook	Negative watch list	Positive watch list	Total	%
Fitch	175	98	11	82	45	63	27	501	22%
Moody's	199	116	28	88	71	190	106	798	35%
S&P	252	157	96	80	132	183	87	987	43%
Total	626	371	135	250	248	436	220	2286	100%
BY ISSUER TYPE									
Type	Downgrade	Upgrade	Positive Outlook	Stable Outlook	Negative Outlook	Negative watch list	Positive watch list	Total	%
Financial	143	114	68	53	99	85	59	621	27%
Corporate	483	257	67	197	149	351	161	1665	73%
Total	626	371	135	250	248	436	220	2286	100%

Table 2

Summary statistics

This table reports summary statistics of the sample. The top panel reports the yearly distribution of mean and median rating by year expressed in a transformed scale where 1 indicates the top rating (AAA for S&P and FITCH, Aaa for Moody's) and 24 is the lowest observed rating (CC-); the second panel reports the sample distribution of rating changes expresses in notches where 0 indicates a confirmed rating; The third panel reports the mean median time to watchlist resolution from watchlist inclusion measured in days, where the resolution of a watchlist is either a removal or a rating action. The bottom panel reports mean values of target prices and medians in parentheses.

Distribution of ratings

	-5	-4	-3	-2	-1	0	1	2	3	4
Obs.	1	4	16	100	707	250	441	29	4	2
Frequency	0.06	0.26	1.03	6.44	45.5	16.09	28.38	1.87	0.26	0.13

Mean rating by Year

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Mean	10.10	10.68	11.51	11.48	12.09	11.73	11.07	9.16	9.98	10.35
Median	11	11	11	11	11	11.5	11	8	10	10

Duration of Watchlist

	Mean	Median
Positive Watchlist to Upgrade	91	70
Negative Watchlist to Downgrade	105	93
Total	96	76

Target price

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Mean	53.12	43.05	40.04	48.98	72.01	68.27	91.11	106.38	81.72	64.53
Median	(50)	(41)	(35)	(33)	(39)	(42)	(45)	(55)	(44)	(34)

Table 3

Changes in target prices

This table reports the average observed changes in Target Prices by notches of rating change across different windows. We report changes in target prices in terms of ACTP i.e. the average change in target price prior to the credit event. ACTP is computed as follows: first, for each company we compute the average of changes in the target prices by the same analysts before the same credit event. Secondly we calculate the average of all changes for homogeneous rating revision. We compute this measures for 3 windows before the credit event and three forward windows after the credit event.

	Rating change								
	-5	-4	-3	-2	-1	0	1	2	3
ACTP-120	-30.60%	-20.38%	-13.37%	-11.25%	-7.90%	0.56%	4.75%	9.84%	10.87%
ACTP-90	-36.90%	-17.28%	-16.75%	-11.54%	-7.72%	0.18%	4.53%	10.26%	15.63%
ACTP-60	-40.00%	-33.88%	-17.79%	-11.12%	-7.70%	0.70%	4.81%	8.90%	16.67%
ACTP+60	14.30%	11.58%	-8.34%	-0.95%	-1.85%	5.01%	4.30%	8.52%	NA
ACTP+90	14.30%	11.93%	-4.13%	0.55%	-1.57%	4.39%	4.21%	7.53%	NA
ACTP+120	-9.40%	6.13%	0.59%	2.32%	-0.98%	4.21%	4.19%	7.42%	NA

Table 4

Linear Regressions

This table reports linear regressions of the changes in target prices and rating actions. The first three regressions' dependent variable is the rating action conditional on different computation window of the independent variable, the average change in target price (ACTP). The last three regressions test the direction of causality assessing the effects of a rating action on target prices published after the rating action. Standard errors are reported in parentheses. Significance at 10%, 5% and 1% level is denoted by by *, ** and *** respectively.

Model	Dep Var	Indep Var	Intercept	Parameter	adj-R^2	F-test
1	Rating Change	CTP-120	-0.194***	3.693***	0.214	399.6
			(0.0254)	(0.185)		
2	Rating Change	CTP-90	-0.203***	3.348***	0.194	353.4
			(0.0257)	(0.178)		
3	Rating Change	CTP-60	-0.219***	2.916***	0.175	307.7
			(0.0260)	(0.166)		
4	CTP+60	Rating Change	0.0205***	0.0262***	0.0299	44.13
			(0.004)	(0.004)		
5	CTP+90	Rating Change	0.0203***	0.0219***	0.0263	39.18
			(0.004)	(0.003)		
6	CTP+120	Rating Change	0.0228***	0.0183***	0.0207	30.84
			(0.004)	(0.003)		

Table 5

Univariate multinomial logistic regressions

This table presents the results of multinomial logistic regressions of the likelihood of a rating action following changes in the target price of the borrower in the 60, 90 and 120 days windows before the credit event. The dependent variable is the notch change in the rating and takes values ranging from -5 to +3. The independent variable is the Change in Target Price (CTP) calculated as the change in target price issued by all analyst on each firm prior to each rating action. The baseline rating action in all models is 0=confirmed rating. Standard errors are reported in parentheses. ***,**,* denote statistical significance at the 1%,5%, and 10% levels respectively.

	Rating actions										
	Downgrades					Upgrades					
	-5	-4	-3	-2	-1	1	2	3	Pseudo R^2	Chi ^{2}	N.
	Model 1-CTP120 days								0.0979	382.84***	1462
Intercept	-8.384***	-5.391***	-3.362***	-1.395***	0.813***	0.475***	-2.473***	-4.717***			
	(2.706)	(0.935)	(0.381)	(0.156)	(0.080)	(0.084)	(0.242)	(0.711)			
CTP 120 days	-20.59**	-14.31***	-10.11***	-8.774***	-6.559***	3.422***	6.460***	6.918*			
	(8.292)	(3.943)	(2.154)	(1.087)	(0.730)	(0.771)	(1.534)	(3.849)			
	Model 2-CTP90 days								0.0854	333.6***	1461
Intercept	-8.068***	-4.910***	-3.545***	-1.362***	0.847***	0.491***	-2.467***	-4.937***			
	(2.157)	(0.783)	(0.405)	(0.154)	(0.080)	(0.084)	(0.244)	(0.789)			
CTP 90 days	-17.37***	-10.55***	-10.29***	-7.591***	-5.373***	3.046***	6.202***	8.331**			
	(5.421)	(3.536)	(1.941)	(1.006)	(0.671)	(0.708)	(1.479)	(3.495)			
	Model 3-CTP60 days								0.0765	294.57***	1443
Intercept	-7.769***	-5.889***	-3.514***	-1.287***	0.876***	0.482***	-2.362***	-4.910***			
	(2.122)	(0.975)	(0.396)	(0.148)	(0.079)	(0.084)	(0.233)	(0.789)			
CTP 60 days	-14.88***	-13.54***	-9.093***	-6.453***	-4.822***	2.377***	4.357***	7.146**			
	(4.806)	(2.642)	(1.719)	(0.919)	(0.619)	(0.642)	(1.392)	(3.265)			

Table 6

Multivariate multinomial logistic regressions

This table presents the results of a set of multivariate multinomial logistic regressions of the likelihood of a rating action following changes in the target price of the borrower in the120 days windows before the credit event restricting the response variable to -1,0 or 1 which indicates a one notch downgrade, an unchanged rating or a one-notch upgrade. Model 1 present results for the complete set of observations; Model 2 present results for the Financials and Industrials groups; Model 3 presents individual results for rating actions issued by S&P, Moody's and Fitch respectively. The independent variables are the Change in Target Price (CTP) calculated as the change in target price issued by all analyst on each firm prior to each rating action, the stock price change in the same window before the rating action and the numerical transformation of the previously outstanding rating issued on the same firm by the same rating agency. The additional independent variables are as follows: Country controls for the issuer's country of incorporation, Rating Agency controls for the rating issuer, year controls for market cycle effects, Investment grade controls for the initial rating family. The baseline rating action in all models is 0=confirmed rating. Change in probability reports the estimated change in probability for each response category conditional on the independent changing from -1/2 standard deviations from its average to +1/2 standard deviation above its average. Standard errors clustered at the year level are reported in parentheses.

	Model 1				Model 2				Model 3					
	Restricted				Financials		Industrial		S&P		Moody's		Fitch	
	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1
Intercept	0.124	-2.845***	1.008***	-1.899***	3.719***	-0.949**	0.647**	-1.377***	1.366***	-1.728***	0.237	-2.416***	-0.0469	-2.300***
	(0.223)	(0.419)	(0.194)	(0.434)	(0.725)	(0.421)	(0.276)	(0.274)	(0.217)	(0.638)	(0.463)	(0.381)	(0.157)	(0.480)
CTP 120 days	-6.470***	2.404**	-8.691***	-1.003	-5.317**	4.070	-9.771***	-2.203	-10.94*	-3.226	-8.080***	-1.455	-9.069***	2.405
	(0.888)	(1.027)	(1.822)	(1.909)	(2.729)	(5.383)	(2.716)	(2.645)	(5.791)	(4.657)	(2.988)	(3.802)	(1.675)	(4.586)
Change in probability from -s/2 to +s/2 of CTP 120 days	-0.232	0.231	-0.210	0.210	-0.190	0.189	-0.177	0.176	-0.189	0.188	-0.166	0.166	-0.169	0.168
Stock price change 120 days			0.910	1.908**	0.842	1.908	0.721	1.997	1.916	2.707	1.084	1.783	-0.417	1.551
			(1.510)	(0.830)	(2.157)	(1.937)	(1.655)	(1.253)	(1.843)	(1.698)	(1.679)	(1.491)	(2.120)	(1.188)
Previous rating action			-0.141	0.318**	0.120	0.192	-0.189	0.373***	0.256	0.630***	-0.0438	0.502*	-0.598***	0.0142
			(0.165)	(0.143)	(0.370)	(0.359)	(0.162)	(0.131)	(0.256)	(0.237)	(0.354)	(0.285)	(0.136)	(0.127)
COUNTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
RATING AGENCY	YES	YES	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
INVESTMENT GRADE	YES	YES	YES	YES	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.314		0.321		0.447		0.314		0.348		0.360		0.372	
Chi ^{2}	844.5													
N.observations	1324		865		258		607		406		245		214	

Table 7

Watchlist and outlook effects

This table presents the results of a set of multivariate binomial logistic regressions controlling for the effects of the release of additional statements by the rating agencies. Model 1 present the estimated parameters for upgrades and downgrades issued in isolation; Model 2 present results for rating actions issued jointly with adddiitional statements (watchlist, outlook, or both); Model 3 estimates parameters only for watchlist inclusions issued in isolation; Model 4 present results for rating actions preceded by a watchlist issued by the same agency (contaminated)and including only actual upgrade or downgrade; Model 5 shows estimates for uncontaminated rating actions, i.e. actions not anticipated by a watchlist and including only actual upgrade or downgrade. In all models we restrict the response variable to -1 or 1 where -1 indicates a negative change (negative watchlist or one-notch downgrade) or a positive change (positive watchlist or one-notch upgrade). The independent variable is the Change in Target Price (CTP) calculated as the change in target price issued by all analyst on each firm in the120 days windows before the credit event. For robustness purposes we also adopt the 60 days window in Model 4. The additional independent variables are dummies definied as follows: Country controls for the issuer's country of incorporation, Rating Agency controls for the rating issuer, year controls for market cycle effects, Investment grade controls for the initial rating family. The baseline rating action in all models is 1=positive change. Change in probability reports the estimated change in probability for each response category conditional on the independent changing from -1/2 standard deviations from its average to +1/2 standard deviation above its average. Standard errors clustered at the year level are reported in parentheses. ***,**,* denote statistical significance at the 1%,5%, and 10% levels respectively.

	Model 1	Model 2	Model 3	Model 4		Model 5
	Single	Multiple	Watchlist	Contaminated rating actions	Contaminated rating actions	Uncontaminated rating actions
	-1	-1	-1	-1	-1	-1
Intercept	2.190***	18.84***	3.666***	3.889***	4.416***	1.945***
	(0.389)	(1.816)	(0.464)	(1.182)	(0.729)	(0.335)
CTP 120 days	-8.107***	-17.01***	-9.304***	-8.573***		-9.742***
	(0.919)	(5.082)	(1.946)	(1.764)		(2.307)
CTP 60 days					-6.817***	
					(2.133)	
Change in probability from -s/2 to +s/2 of CTP 120 days	-0.195	-0.014	-0.176	-0.096	-0.097	-0.254
Stock price change 120 days	-1.472	-0.334	-0.866	-1.592		-1.265
	(1.475)	(4.451)	(0.939)	(1.871)		(0.941)
Stock price change 60 days					-1.972*	
					(1.145)	
Previous rating action	-0.742***	-0.868***		-0.625***	-0.631***	-0.911***
	(0.227)	(0.136)		(0.169)	(0.186)	(0.335)
COUNTRY	YES	YES	YES	YES	YES	YES
RATING AGENCY	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
INVESTMENT GRADE	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.389	0.513	0.270	0.505	0.377	0.444
Chi ^{2}						
N.observations	454	108	464	259	219	341

Table 8

Firm-level characteristics

This table presents the results of a set of multivariate multinomial logistic regressions of the likelihood of a rating action following changes in the target price of the borrower in the120 days windows before the credit event and controlling for firm level characteristics. We restrict the analysis to Industrial companies only and to the -1,0 or 1 outcomes of the dependent variable that indicate a one-notch downgrade, an unchanged rating or a one notch upgrade respectively. The firm-level variables are: Leverage computed as in Baker and Wurgler (2001) as follows: book debt is defined as total assets (COMPUSTAT Annual Item 6) minus book equity given by total assets less total liabilities (Item 181) and preferred stock (Item 10) plus deferred taxes (Item 35) and convertible debt (Item 79). Book leverage is then defined as book debt to total assets. Market leverage defined as book debt divided by the result of total assets minus book equity plus market equity defined as common shares outstanding (Item 25) times price (Item 199). Tangibility computed following Berger et al (1996) and Campello (2007) as Tangibility = 0.715 Receivables ? + 0.547 Inventory ? + 0.535 Capital ? where Receivables is COMPUSTAT's item #2, Inventory is item #3, and Capital is item #8. Tangibility is scaled by total assets. Volatility is defined as the weekly standard deviation of common equity prices in the 6 months before each rating event. We also include year, agency, investment gradeand country fixed-effects. The baseline rating action in all models is 0=confirmed rating. Robust standard errors clustered by year are reported in parentheses. ***,**,* denote statistical significance at the 1%,5%, and 10% levels respectively.

	Base Model		Model 1		Model 2		Model 3		Model 4	
	-1	1	-1	1	-1	1	-1	1	-1	1
Intercept	-0.123	-2.281***	-3.435***	-1.238	-4.008***	-0.924	-2.082*	-0.118	-3.989***	-1.266
	(0.256)	(0.445)	(1.012)	(1.267)	(1.116)	(1.065)	(1.212)	(1.501)	(1.128)	(1.083)
CTP 120 days	-7.336***	0.727	-7.491***	1.166	-12.31*	7.272***	-9.806**	9.687***	-12.40***	6.900*
	(1.118)	(1.189)	(1.630)	(0.757)	(6.732)	(2.791)	(4.558)	(3.651)	(4.245)	(3.728)
Leverage			9.648***	-2.903	10.90***	-3.592	6.818**	-5.900	10.87***	-2.625
			(3.476)	(4.855)	(3.443)	(4.513)	(3.338)	(4.349)	(3.707)	(3.558)
Leverage^2			-6.235**	1.501	-6.862**	2.100	-7.382**	3.140	-6.795**	1.682
			(2.961)	(4.233)	(2.875)	(3.861)	(3.100)	(3.793)	(3.009)	(3.016)
CTP*Leverage					6.403	-9.397***	8.078	-9.465**	6.473	-9.075
					(7.123)	(3.644)	(6.904)	(3.819)	(6.146)	(5.666)
Tangibility/TA							-7.394*	-1.718		
							(4.210)	(3.126)		
CTP*(Tangibility/TA)							-11.19	-7.002		
							(8.921)	(11.924)		
Leverage*(Tangibility/TA)							16.22**	3.812		
							(6.653)	(5.046)		
Volatility									-0.006	0.021
									(0.021)	(0.026)
Volatility*Leverage									0.005	-0.041
									(0.030)	(0.038)
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.301		0.323		0.330		0.34		0.334	
N.observations	931		931		931		931		931	

Table 9
Financial Crisis

This table presents the results of a set of multivariate multinomial logistic regressions of the likelihood of a rating action following changes in the target price of the borrower in the120 days windows before the credit event restricting the response variable to 1,0 or 1 which indicates a one-notch downgrade, an unchanged rating or a one notch upgrade. We present separate results for the three years around the crisis and for the 2007-2009 period. The independent variable is the Change in Target Price (CTP) calculated as the change in target price issued by all analyst on each firm prior to each rating action. The additional independent variables are as follows: Country controls for the issuer's country of incorporation, Rating Agency controls for the rating issuer, year controls for market cycle effects, Investment grade controls for the initial rating family. The baseline rating action in all models is 0=confirmed rating. Standard errors are reported in parentheses. ***,**,* denote statistical significance at the 1%,5%, and 10% levels respectively.

	CRISIS		2007		2008		2009	
	-1	1	-1	1	-1	1	-1	1
Intercept	-0.111	-0.385*	-0.272	-0.330	-0.696*	-0.121	0.248	-2.177***
	(0.201)	(0.226)	(0.462)	(0.434)	(0.418)	(0.409)	(0.299)	(0.738)
CTP 120 days	-6.669***	2.517**	-16.64***	8.988**	-13.96***	4.686*	-4.113***	-4.890
	(0.914)	(1.017)	(4.646)	(3.950)	(2.759)	(2.493)	(1.047)	(3.392)
COUNTRY	YES	YES	YES	YES	YES	YES	YES	YES
RATING AGENCY	YES	YES	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES	YES	YES
INVESTMENT GRADE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.153		0.263		0.248		0.139	
Chi ^{2}	209.0		105.3		106.4		56.59	
N.observations	662		186		209		267	

Table 10

MIR Global sample descriptive and summary statistics

This table reports summary statistics of the Moody's Implied ratings Global Sample. The statistics have been computed on the subsample of 16,324 observations for which a rating action was available. All data are presented at the Region level. In Panel A we report the number of unique companies in the sample, the number or rating actions, the breakdown of rating actions and the number of distinct MIR available 120 days before the rating action. Panel B reports the yearly distribution of RAs. Panel C reports the sample breakdown by credit Grade, computed before each rating action, and the industry distribution of rating actions.

PANEL A

Region	Unique Companies	RA	Downgrades	Upgrades	Debt MIR	Equity MIR	CDS MIR
Americas	3,364	11,207	6,999	4,208	5292	4135	2777
Asia	395	1,087	502	585	309	327	365
EMEA	1,216	3,379	1,965	1,414	1281	860	1177
Japan	286	651	239	412	305	392	376
Total	5,261	16,324	9,705	6,619	7187	5714	4695

PANEL B

Region	2003	2004	2005	2006	2007	2008	2009
Americas	834	903	892	3,349	2,311	1,170	1,748
Asia	117	69	93	213	234	103	258
EMEA	303	222	324	711	743	390	686
Japan	44	126	63	116	134	40	128
Total	1,298	1,320	1,372	4,389	3,422	1,703	2,820

PANEL C

			Industry			
Region	Investment grade	Speculative grade	BFI	Utilities	Industrial	Transportation
Americas	3,131	8,076	2370	883	7,704	250
Asia	626	461	528	99	418	42
EMEA	2,026	1,353	1481	170	1,607	121
Japan	581	70	316	43	278	14
Total	6,364	9,960	4695	1,195	10,007	427

Table 11

Multivariate multinomial logistic regressions on Moody's Global sample using MIR

This table presents the results of a set of multivariate multinomial logistic regressions of the likelihood of a rating actionobserved on any company in the Global sample, following changes in Moody's Implied rating computed on the Debt (Model 1), Equity (Model 2) and CDS market (Model 3) in the120 days windows before the credit event. We restricting the response variable to -2,-1, 1, and 2 which indicate a two or one notch downgrade, and a one or two notch upgrade respectively. The sample is 16,324 rating actions on 5264 companies listed in global markets. The additional independent variables are as follows: Previous Rating Action controls for the sign and size of the previous rating action on the same company; Region controls for the issuer's global Region: Americas (north and South), Asia, EMEA and Japan; Year controls for market cycle effects, Investment grade controls for the initial rating family. The baseline rating action in all models is 2=two notch change. Change in probability reports the estimated change in probability for each response category conditional on the independent changing from -1/2 standard deviations from its average to +1/2 standard deviation above its average. Standard errors clustered at the year level are reported in parentheses. ***,**,* denote statistical significance at the 1%,5%, and 10% levels respectively.

	Model 1			Model 2			Model 3		
	Debt MIR			Equity MIR			CDS MIR		
	-2	-1	1	-2	-1	1	-2	-1	1
Intercept	0.0139	1.105**	1.353***	0.883*	1.796***	2.091***	0.685	1.403**	0.783**
	(0.751)	(0.541)	(0.299)	(0.454)	(0.358)	(0.196)	(0.617)	(0.566)	(0.360)
Moody's MIR predicted change	-0.542***	-0.409***	-0.0684**	-0.257***	-0.191***	-0.0142	-0.551***	-0.464***	-0.104***
	(0.069)	(0.056)	(0.033)	(0.059)	(0.048)	(0.016)	(0.092)	(0.092)	(0.038)
Change in probability from -s/2 to +s/2 of MIR predicted change	-0.069	-0.165	0.192	-0.052	-0.123	0.147	-0.068	-0.192	0.201
Previous rating action	0.379*	0.460**	0.263***	0.528***	0.568***	0.294***	0.335*	0.379**	0.179**
	(0.200)	(0.212)	(0.082)	(0.192)	(0.169)	(0.087)	(0.179)	(0.160)	(0.077)
REGION	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES
INVESTMENT GRADE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2		0.148			0.133			0.164	
Chi ^{2}									
N.observations		6774			5426			4401	

Figure 1

Changes in Target Prices and rating actions

Figure 1 reports regression lines and scatter plots of the average change in target price for three different computation windows: 60, 90 and 120 days. The vertical axis reports the associated changes in rating.

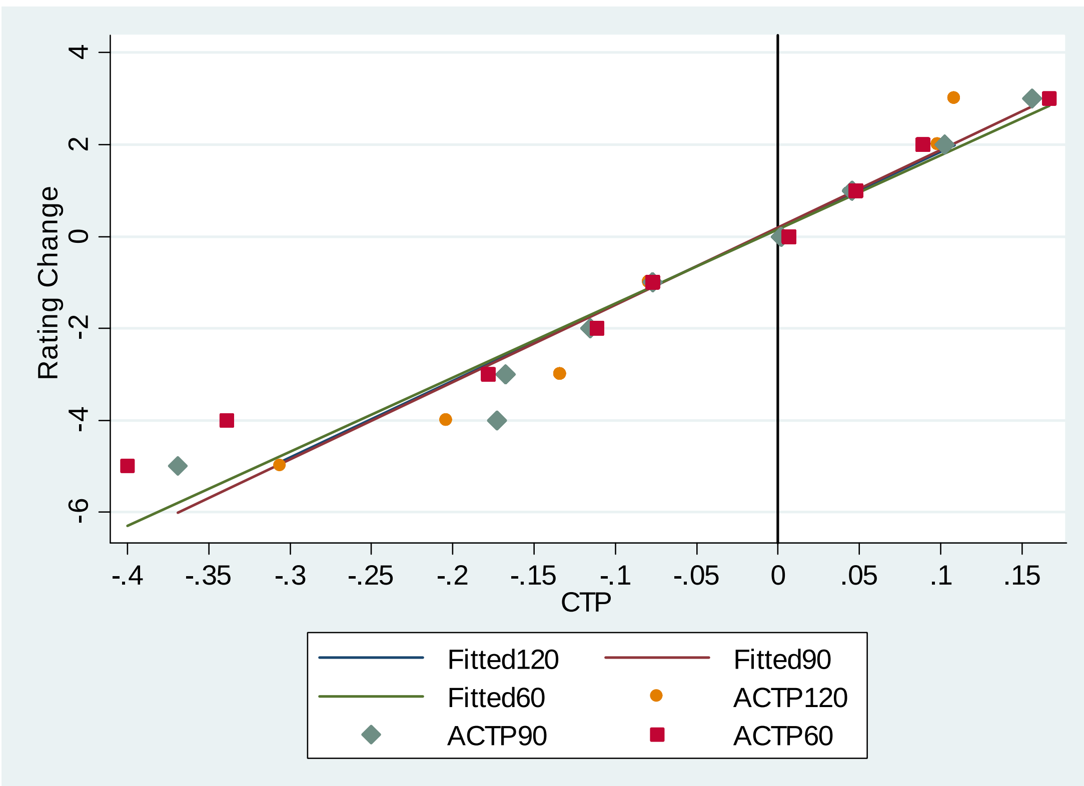


Figure 2

Rating changes estimated probabilities

Figure 2 plots estimated probabilities of a rating event conditional on changes in target prices. estimated probabilities are obtained from the restricted multinomial logistic regression in Table 6.

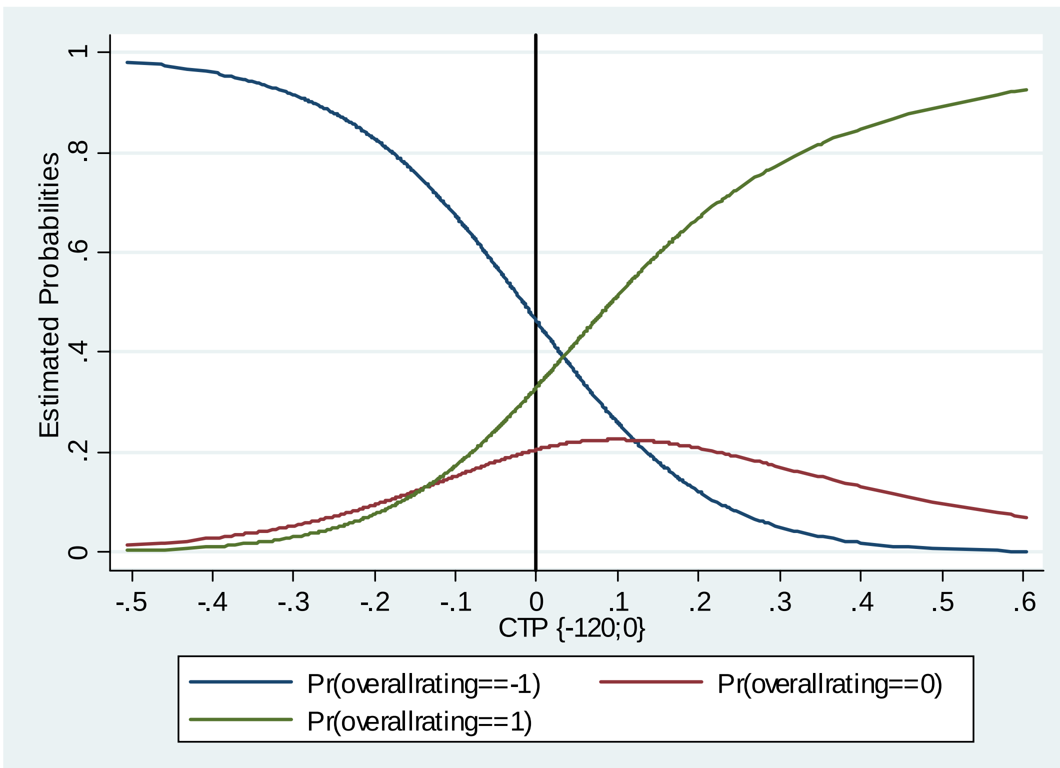


Figure 3

Distribution of changes in target prices neutral rating actions

Figure 3 reports the empirical distribution of the changes in target prices for the 120 days window before neutral rating actions, i.e. rating confirmed. The dashed line reports the standard normal density function while the green line plots the kernel density function.

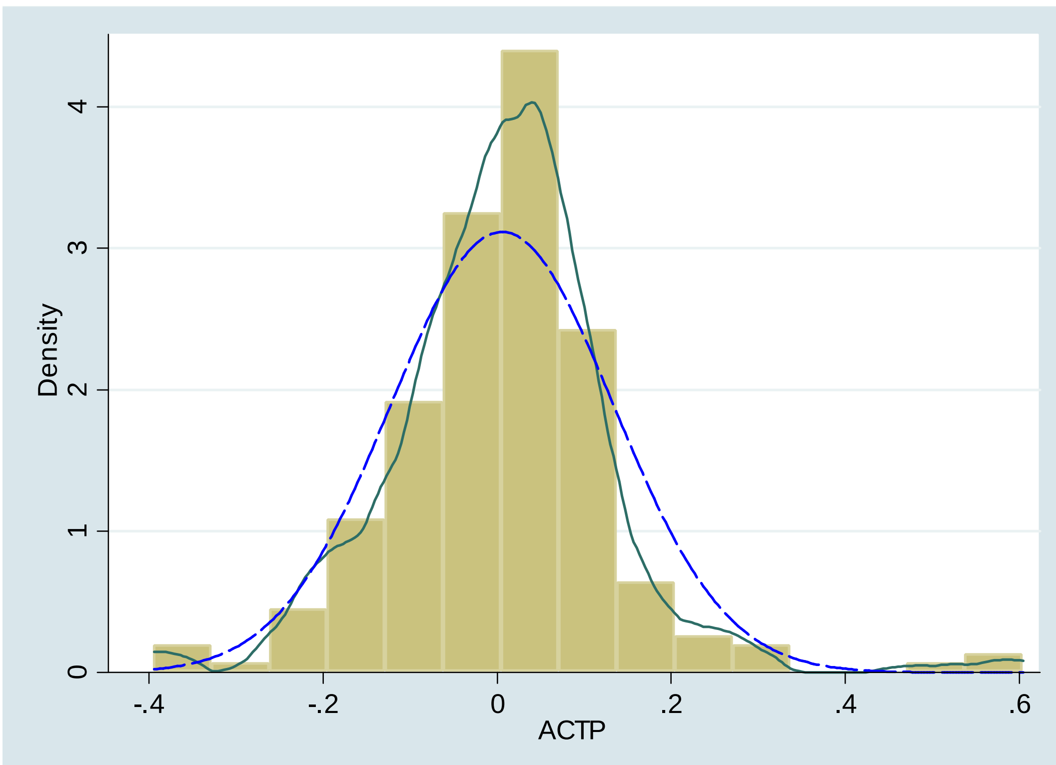


Figure 4

Evolution of rating and changes in target prices

Figure 4 reports the yearly distribution of average rating and the average change in target prices over the sample period.

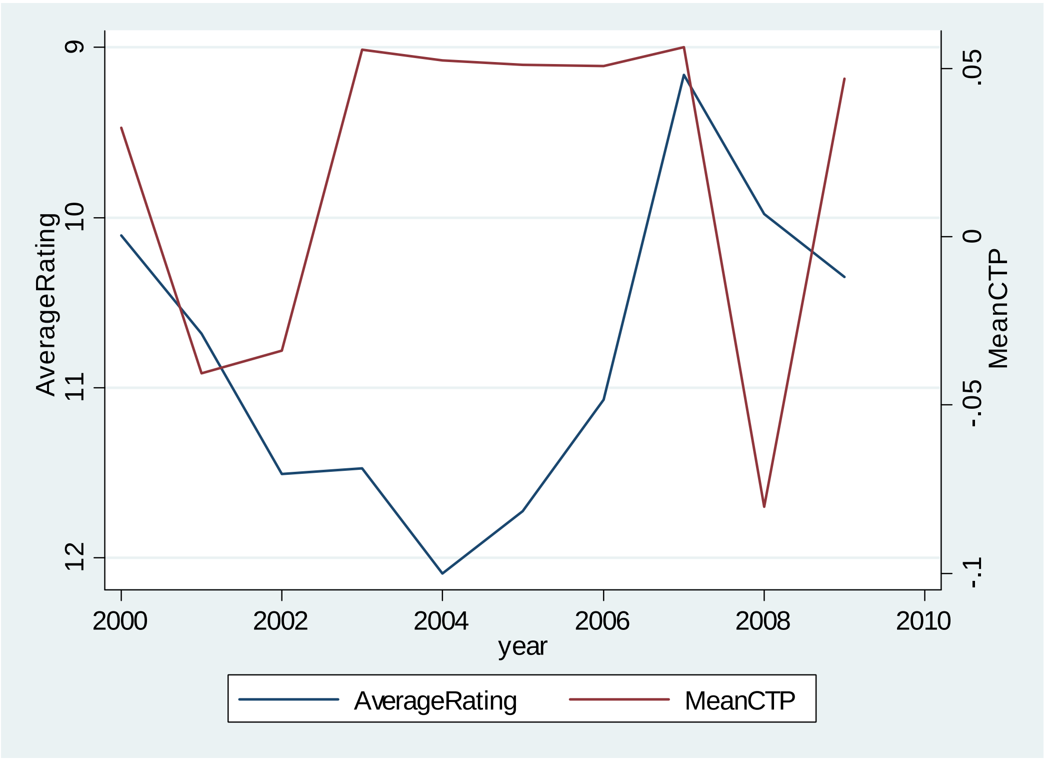
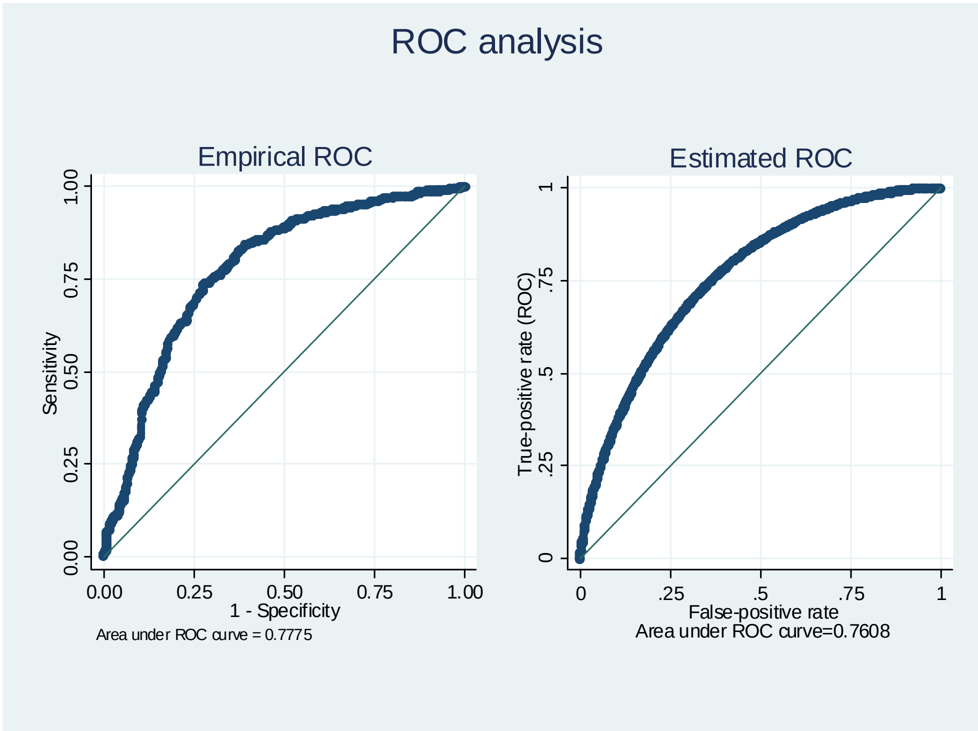


Figure 5

Receiver Operating Characteristics Analysis

This figure reports the empirical and estimated ROC curves using CTP (Top Panel) and MIR (Bottom Panel) as predictors. The estimated curves have computed through a probit function with maximum likelihood.



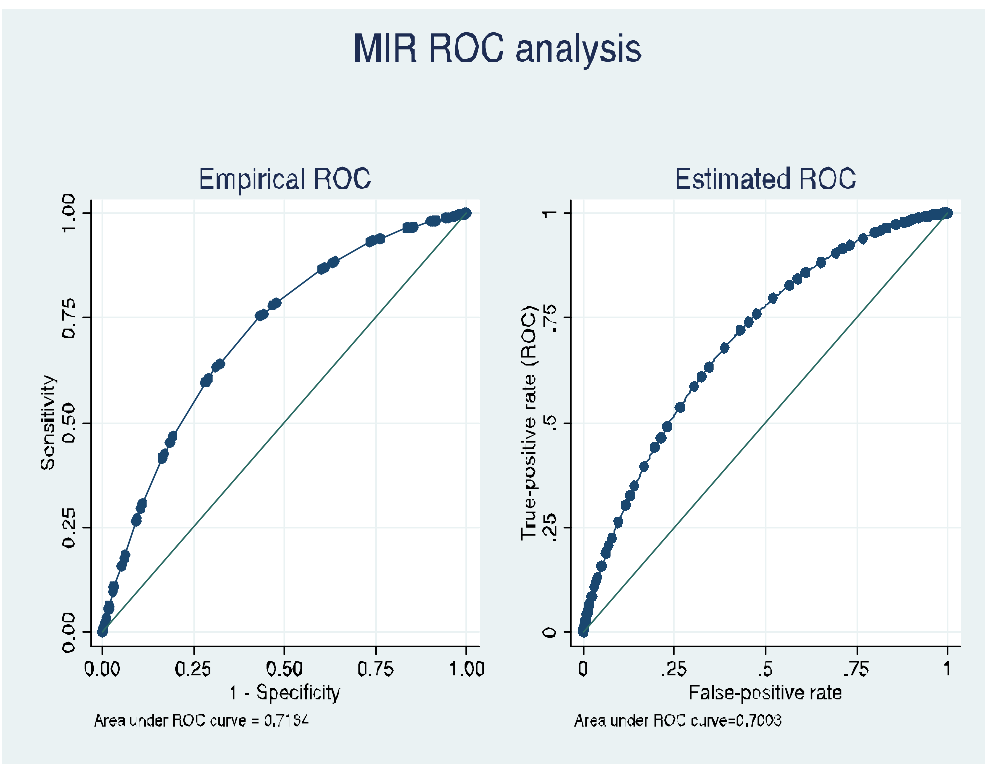


Figure 6

Trading volume

This figure reports the cross-sectional abnormal trading volume around negative rating events (downgrades) in percentage terms. Abnormal trading volume is computed as (Daily trading volume/Average trading volume). A level of 1 (captured by the horizontal solid red line) indicates a tradaing volume equal to the historical average. The dashed line indicates the pre-event average abnormal volume. The dashed line indicates the post-event average trading volume. Pre-event average trading volume is 48% above average and post-event trading volume is 40% below average. The difference is significant at the 0.1% level.

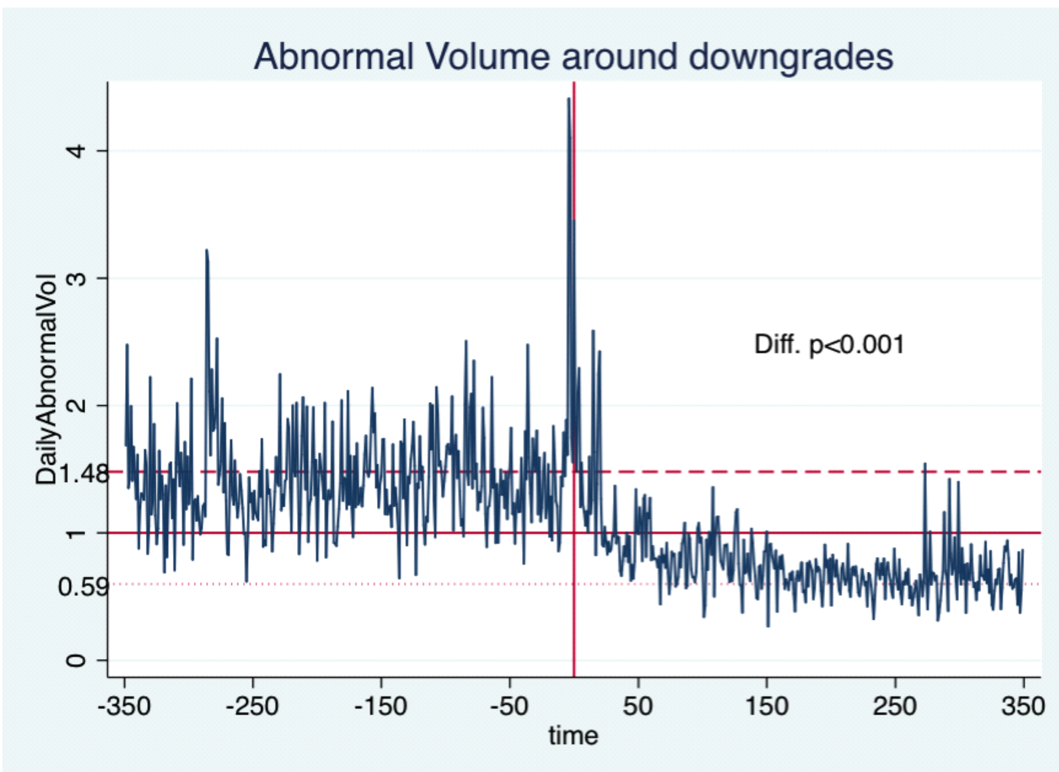


Figure A1

Evolution of average rating and target prices.

Figure 4 reports the yearly distribution of average rating and the average target prices over the sample

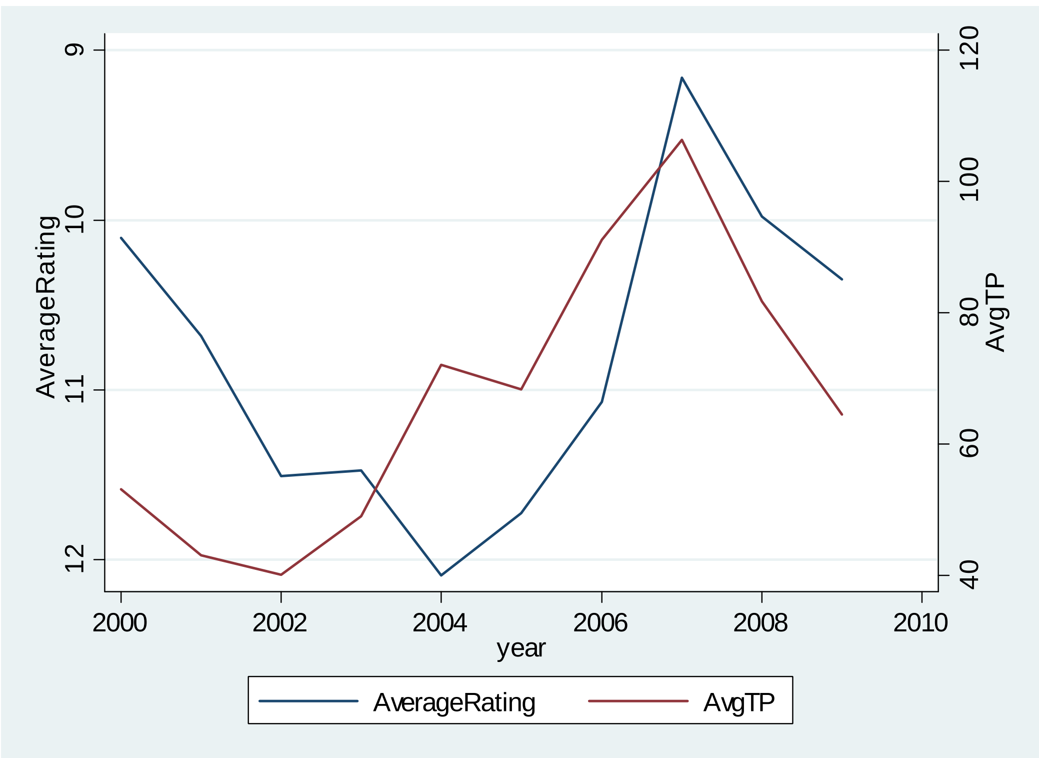


Table A1

Multivariate multinomial logistic regressions on Moody's subsample using MIR

This table presents the results of a set of multivariate multinomial logistic regressions of the likelihood of a rating action following changes in Moody's Implied rating computed on the Debt (Model 1), Equity (Model 2)and CDS market (Model 3) restricting the response variable to -1,0 or 1 which indicates a one notch downgrade, an unchanged rating or a one-notch upgrade. The sample is the Moddy's subsample of the observations for which we had computed a CTP. Model 1 present results for the complete set of observations; Model 2 present results for the Financials and Industrials groups; Model 3 presents individual results for rating actions issued by S&P, Moody's and Fitch respectively. The independent variable is the MIR predicted change computed as the MIR minus the current rating observed 120 days before the rating event . The additional independent variables are as follows: Country controls for the issuer's country of incorporation, Rating Agency controls for the rating issuer, year controls for market cycle effects, Investment grade controls for the initial rating family. The baseline rating action in all models is 0=confirmed rating. Change in probability reports the estimated change in probability for each response category conditional on the independent changing from -1/2 standard deviations from its average to +1/2 standard deviation above its average. Standard errors clustered at the year level are reported in parentheses. ***,**,* denote statistical significance at the 1%,5%, and 10% levels respectively.

	Model 1				Model 2				Model 3			
	Debt MIR				Equity MIR				CDS MIR			
	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1
Intercept	-0.013	-3.880***	-0.156	-3.202***	-0.031	-3.337***	-0.022	-3.270***	-0.174*	-4.076***	-0.056	-3.755***
	(0.181)	(0.256)	(0.133)	(0.226)	(0.158)	(0.227)	(0.155)	(0.354)	(0.092)	(0.271)	(0.108)	(0.489)
Moody's MIR predicted change	-0.221	0.500***	-0.219**	0.422***	-0.087***	0.136***	-0.108**	0.156***	-0.221	0.452***	-0.348**	0.433***
	(0.182)	(0.102)	(0.109)	(0.135)	(0.029)	(0.023)	(0.054)	(0.040)	(0.157)	(0.061)	(0.168)	(0.087)
Change in probability from -s/2 to +s/2 of MIR predicted change	-0.231	0.229	-0.214	0.211	-0.145	0.144	-0.18	0.178	-0.231	0.229	-0.276	0.272
Stock price change 120 days			-1.841*	1.810*			-1.742***	2.654***			-1.496**	1.073**
			(1.087)	(1.093)			(0.612)	(0.756)			(0.618)	(0.420)
Previous rating action			-0.090	0.497***			-0.088	0.548***			0.031	0.432***
			(0.068)	(0.154)			(0.087)	(0.087)			(0.079)	(0.126)
COUNTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
INVESTMENT GRADE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.342		0.382		0.305		0.372		0.353		0.405	
Chi ^{2}												
N.observations	244		191		298		228		301		231	