# Information Effects of Bond Rating Changes: The Role of the Rating Prior to the Announcement


Philippe Jorion

and

Gaiyan Zhang

Paul Merage School of Business

University of California at Irvine


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Correspondence can be addressed to:

Philippe Jorion
Paul Merage School of Business
University of California at Irvine,
Irvine, CA 92697-3125
Phone: (949) 824-5245, E-mail: pjorion@uci.edu

Gaiyan Zhang
College of Business
University of Missouri-St.Louis
St. Louis, MO 63121-4400
314-516-6269, zhangga@umsl.edu

# Information Effects of Bond Rating Changes: The Role of the Rating Prior to the Announcement


**ABSTRACT**

This paper shows that studies of announcement effects of bond rating changes should take into account the rating prior to the announcement. First, we provide theoretical support for different price effects as a non-linear function of the prior credit rating, using a structural, Merton-type model linking the change in default probability to the change in the stock price. Next, we show that this theoretical prediction is verified in the empirical data. We find much stronger information effects, measured by stock price effects, for rating changes for low-rated firms relative to high-rated firms. Accounting for the role of the rating prior to the announcement explains in large part the puzzling empirical regularity that stock price effects are associated with downgrades but not upgrades. In addition, it eliminates the investment-grade barrier effect reported in previous studies.



JEL Classifications: G18, G14, G28, K22

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# I. INTRODUCTION

Recent developments in credit risk models have spurred an increased scrutiny of the informativeness of bond credit ratings. This reflects current technological advances in credit risk modeling, partly stimulated by the Basel Committee on Banking Supervision (BCBS), which has now instituted capital charges for credit risk based on credit ratings.[1]

The informativeness of bond credit ratings can be measured in a number of ways. One approach relates credit ratings to the frequency of default within the same rating class.[2] Alternatively, a large body of literature has investigated the information content of changes in credit ratings, measured in terms of abnormal stock returns around the announcement.[3] If credit ratings changes are informative, we would expect a significant stock price reaction: Good news about a company's cash flows should affect its bond and stock prices in the same direction. This can be extended to cross-sectional regressions, which examine the effect of other factors such as the business cycle, structural changes in the information environment, the rationale for the rating change, and so on.

So far, however, extant empirical studies have not focused on the importance of the credit rating prior to the change (henceforth, "prior rating"). The contribution of this paper is two-fold. First, we provide theoretical support for different price effects as a non-linear function of the credit rating prior to the announcement, using a structural, Merton-type model linking the change in default probability to the change in the stock price. Second, we provide strong empirical evidence

[1] The so-called "Basel 2" rules, BCBS (2004), which apply to global commercial banks, were finalized in June 2004. The simplest approach, which is likely to be the most widely used, establishes capital adequacy requirements based on ratings provided by external credit rating agencies. More advanced approaches allow banks to use their internal ratings.
[2] This statistical analysis is typically performed by the credit rating agencies, e.g. Moody's (2003) and S&P (2004).
[3] See for instance, Holthausen and Leftwich (1986), Hand et al. (1992), Goh and Ederington (1993), Ederington and Goh (1998), Dichev and Piotroski (2001). Some studies, such as the latter, analyze long-run excess returns after the rating changes. This is not the focus of our study, however. When studying long-run excess returns, the specification of the risk adjustment is crucial. This is not an issue, however, for the announcement effect, which is over a very short window.

that the rating prior to the announcement is extremely important for predicting the size of the stock price reaction. We find much stronger stock price effects for bond rating changes for low-rated firms relative to high-rated firms.

Thus, the prior rating is an important omitted variable that should be taken into account in cross-sections, for at least two reasons. First, the addition of this variable will improve the explanatory power, increase the R-square, and thus the precision of estimated coefficients for other variables of interest. Second, adding this variable will decrease the possibility of erroneous inferences due to a correlation between some other variable of interest included in the regression and the omitted prior rating.

Importantly, this paper shows that this effect in large part explains the observed difference between the informativeness of downgrades and upgrades. Empirically, downgrades have an economically large and statistically significant impact on daily stock prices. Upgrades, however, have a much more muted effect, which is puzzling.[4] The first paper to report this effect with daily data is by Holthausen and Leftwich (1986). They use a sample of 637 ratings changes across classes by Moody's and S&P over the 1977-82 period. In the case of downgrades, they report a 2-day abnormal average return of –2.66 percent, which is large and statistically significant. Upgrades are associated with an abnormal return of +0.08 percent, which is not significant. More recent studies, such as Dichev and Piotroski (2001), indicate that upgrades have recently become

[4] Many empirical studies has documented the asymmetry in stock price reactions to credit rating downgrades and upgrades, for example, Griffin and Sanvicente (1982), Holthausen and Leftwich (1986), Hand et al. (1992), Ederington and Goh (1998), Dichev and Piotroski (2001). However, most of these studies do not provide explanations for this empirical regularity. Hand et al. (1992) and Steiner and Heinke (2001) examine the effect of credit rating changes on bond prices. Generally downgrades have a significant price effect, but upgrades do not. Norden and Weber (2004) provide a useful summary of the empirical literature.

statistically significant, although their effect is still smaller than downgrades, typically by a factor of five.[5]

The downgrade effect suggests that ratings agencies provide valuable new information to markets. It is not clear, however, why only negative information should be valuable. Ederington and Goh (1998) argue that this could happen because companies voluntarily release good news to the market but are reluctant to release unfavorable information. This would create a bias toward negative information content for credit ratings changes. Alternatively, rating agencies could expend more resources in detecting deterioration in credit quality rather than improvements due to the higher reputational cost of failing to detect looming credit problems. Regardless of the exact mechanism, such explanations imply that rating upgrades have little information content, which may not be the appropriate conclusion.

Another explanation is the design of the empirical cross-section, which largely ignores the prior value of the rating.[6] This should be an important factor, however. For example, a downgrade from AA− to A+ should have much less information content than a downgrade from BB− to B+. In the former case, the probability of default is very small and is hardly affected. The second case, however, represents a much larger increase in the default probability, is reflected in larger changes in bond yield spreads, and should have a larger impact on stock prices. Accordingly, if downgrades more often start from lower ratings than upgrades, it is not surprising to observe an overall stronger

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[5] Dichev and Piotroski (2001) use all of Moody's announcements over 1970 to 1997, which is a larger sample of 4,727 observations. Although they mainly focus on long-run returns following ratings changes, they also report a 3-day price effect of -1.97 percent for downgrades and +0.48 percent for upgrades. Thus the downgrade effect is much stronger. Both effects are significant in this later study, in part due to the increased power from the larger sample size. The upgrade effect is still much smaller, though, than the downgrade effect.

[6] Some studies, e.g. Hand et al. (1992), separate the sample into investment-grade and speculative-grade to report summary statistics, but assume the same intercept in cross-sections. Goh and Ederington (1999) provide empirical evidence on the stock price response by credit rating but do not adjust for the size of the rating change, which we find to be correlated with the prior rating. Norden and Weber (2004) separate the sample into firms with old rating above and below the median, and find stronger negative effects for downgrade when the old rating is low, which is consistent with our results.

stock price effects for downgrades. Empirically, we do find that the distribution of prior credit ratings is not identical for downgrades and upgrades and that, in addition, downgrades often involve a much bigger change in credit rating than upgrades. This change is correlated with the prior rating. The question is whether the effect of the prior rating can explain the differences between downgrades and upgrades. In a setup accounting for the ratings before and after the changes, we find that upgrades have a non-negligible announcement effect, which is now half that of downgrades. Therefore, the asymmetries between the informativeness of downgrades and upgrades can be largely explained by the effect of prior rating.

Another application is the so-called "investment-grade" effect. Empirically, crossing the investment-grade barrier seems associated with a bigger stock price effect. The argument is that there is something special about this barrier, perhaps due to different clienteles. Presumably, investors restricted to investment-grade bonds are forced to sell bonds that drop into the speculative-grade category, leading to a significant increase in capital costs reflected in the stock price. We show, however, that the significant effect of the "investment grade" variable disappears once the prior rating is added to the regression. In addition, this non-linearity explains the empirical observation in Kwan (1996) that the correlation between stocks and bonds is positive but increases for lower credit ratings. More generally, the prior rating is an important variable that should always be included in cross-sectional studies of bond rating announcements.

The remainder of the paper is organized as follows. Section II links credit ratings and default frequencies. Section III provides a theoretical, Merton-based, model that links the stock price to the default probability and to the credit rating. Section IV presents empirical results. Section V concludes.

## II. CREDIT RATINGS AND DEFAULT FREQUENCIES

A credit rating is an evaluation of creditworthiness, which can be interpreted as probability of default. Table 1 presents the interpretation of credit ratings issued by the two major rating agencies, Standard and Poor's (S&P) and Moody's Investor Service.

[TABLE 1 here]

S&P rates bonds from AAA down to D. Each letter is known as a "class". For the AA to CCC classes, S&P also supplies modifiers, e.g. A+, A, A–. Similarly, Moody's rates bonds from Aaa to C, with modifiers such as A1, A2, A3. We transform the credit rating into a cardinal scale, starting with 1 as AAA, 2 as AA+, and so on.

The agencies also provide statistical studies that relate their credit rating to the frequency of default $P$, based on the analysis of default rates in fixed cohorts.[7] One issue with such studies is that default frequencies are noisy estimates of default probabilities, affected by the sample size. This is especially a problem for high credit ratings, which are associated with low default probabilities. For instance, over the 1981-2002 period, S&P reports a 1-year default rate of 0.00% for AAA to AA, 0.06% for A+, 0.04% for A–, then 0.35% for BBB+. Normally, one would expect default probabilities to increase monotonically as the rating drops. These default rates do not increase uniformly because of sampling variation over short intervals. In contrast, longer horizons give smoother patterns in default rates. This is why we consider default frequencies over a longer period. As an illustration, 10-year default frequencies reported by S&P are displayed in Table 2. Using a longer horizon scales up the frequencies but does not affect our results.

The table demonstrates a central feature of credit rating: a one-notch downgrade or upgrade can correspond to very different changes in the frequency of default. For instance, a downgrade

[7] See also Schuermann and Jafry (2003) for alternative measurements of default probabilities.

from AA− to A+ involves an increase in default frequency of only 0.4% (or 0.016-0.012=0.004). This is not likely to have much of an impact on the stock price. In contrast, a downgrade from BB− to B+ involves an increase in default frequency of 5.0% (or 0.315-0.265-0.050), a much higher number that is more likely to be reflected by a big move in the stock price. Current empirical specifications for the information content of credit rating changes largely ignore this effect.

The table, however, still displays some uneven variation in actual default frequencies. These are further smoothed using the fitted value of a logistic function. Define *P* as the default frequency and *R* as the credit rating scale. The model is

$$\ln(\frac{P}{1-P}) \equiv y = a + bR + \varepsilon \qquad (1)$$

This specification ensures that the resulting probability *P* is between 0 and 1. The fitted default probabilities are then derived from Equation (1), with *a*=-6.069 and *b*=0.377, and are shown in the last column of Table 2. The fit is quite good. We shall use the fitted values of default frequencies in what follows.

[TABLE 2 here]

## III. STOCK PRICES AND DEFAULT PROBABILITY

The goal of this section is to provide a theoretical basis for the non-linear relationship between stock price movements and credit ratings. We first use a structural model to relate changes in stock prices to changes in default probabilities. We then relate these default probabilities to credit ratings, assuming that the change in default probability is entirely unexpected.

The classical approach to capital structure is the Merton (1974) model, which views equity as akin to a call option on the assets of the firm, with an exercise price given by the face value of debt. Although the model has since been generalized, it still gives important insights into the factors affecting capital structure.[8] This class of models abstracts from redistribution of wealth between firm claimants, due for instance to sudden changes in leverage or risk, and predicts that bond and stock prices for the same firm will move in the same direction.[9]

To simplify to the extreme, consider a firm with total value $V$ that has one bond due in one period $T$ with face value $K$. If we assume that markets are frictionless and that there are no bankruptcy costs, the value of the firm is simply the sum of the firm's equity and debt: $V=S+B$. The Merton framework assumes the firm value follows an exogenous stochastic process, given by a geometric Brownian motion

$$d\,V = V\,\mu\,dt + V\,\sigma\,dz \tag{2}$$

If the value of the firm exceeds the promised payment, the bond is repaid in full and stockholders receive the remainder. However, if $V$ is less than $K$, the firm is in default and the bondholders receive $V$ only; the value of equity $S$ goes to zero. The equity is then akin to a call option on the value of the firm. From standard option analysis, and assuming no dividends are paid, the equity value is

$$S = V\,N(d_1) - Ke^{-rT}\,N(d_2) \tag{3}$$

where $N(d)$ is the cumulative distribution function for the standard normal distribution, and

$$d_1 = \ln(V / Ke^{-rT})/\,\sigma\sqrt{T} + (1/2)\,\sigma\sqrt{T}, \quad d_2 = d_1 - \sigma\sqrt{T}$$

This defines a risk-neutral probability that the call will not be exercised, or that the firm will default:

$$P = 1\text{-}N(d_2) = N(-d_2) \tag{4}$$

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[8] This model has since been generalized. For instance, Black and Cox (1976) assume a default-triggering level for the firm's assets whereby default can occur at any time. Longstaff and Schwartz (1995) have a model with a constant default barrier and allow interest rate to follow an Ornstein-Uhlenbeck process. The model, however, has unrealistic assumptions about the default barrier in relation to the face value of the bond. Briys and de Varenne (1997) use a default barrier that grows at the risk-free rate.

We can use this model to relate movements in the stock price to changes in the default probability. Define Φ as the standard normal density function. After simplification, we have

$$\frac{d\ln S}{dP} = \frac{1}{S}\frac{\frac{\partial S}{\partial V}}{\frac{\partial P}{\partial V}} = \frac{1}{S}\frac{N(d_1)}{[-\Phi(d_2)/(V\sigma\sqrt{T})]} = -\frac{V}{S}\frac{N(d_1)\sigma\sqrt{T}}{\Phi(d_2)} \tag{5}$$

Because this coefficient is not constant, the relationship between ln$S$ and $P$ must be non-linear. Changes in the logarithm of the stock price correspond to the stock rate of return used in empirical studies. This is illustrated in Figure 1 using the following parameters: $V$=\$100, $K$=\$100, σ=20%, $r$=5%, $T$=10 years.

[FIGURE 1 here]

Finally, we can put together the structural relationship between the stock price and the default probability, ln$S$=$f$($P$), and the fitted Equation (2), between the default probability and the credit rating, $P$=$f$($R$). We assume the change in default probability is entirely unexpected and reflects a change in the risk-neutral probability.[10] This gives a relationship between the log of the stock price and the credit rating ln$S$=$f$($R$), which is also displayed in Figure 1.

Here, lower credit ratings (higher cardinal scales, or moving to the right) are associated with lower stock prices. For investment-grade credit ratings (above BBB–, which is 10 on this scale), the slope is relatively flat. Thus a downgrade from AAA to AA+ (from 1 to 2) should have much less effect than a downgrade from B to CCC+ (from 16 to 17). Whether this is an important issue is examined next with actual data.

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[9] See Jarrow et al. (2003). Kwan (1996) reports that the correlation between firm-specific stock and bond prices is on average positive, providing support for this class of models.

## IV. EMPIRICAL ANALYSIS

Our ratings sample comes from the Mergent Fixed Investment Securities Database (FISD). The database contains detailed information on over 90,000 U.S. corporate, U.S. Agency and U.S. Treasury debt securities. Debt rating information includes ratings from S&P, Moody's and Fitch since April 1995. We restrict the sample to senior unsecured debt ratings on U.S. domestic taxable corporate bonds. Each bond rating change constitutes one sample observation. In the case of rating changes pertaining to multiple bond issues of the same issuer on the same date, we retain the issue with the largest magnitude of rating change because the issue is likely to result in the strongest impact on stock prices. FISD also provides effective dates for new ratings, which are used as announcement dates for this study.

Our sample selection also requires the availability of daily stock returns for the sample firms to compute abnormal stock returns. The final sample consists of 1195 downgrades and 361 upgrades by Standard & Poor's and Moody's during the period of January 1996 to May 2002. These are matched with abnormal stock returns in a three-day window around the rating change.[11] If a rating is changed consecutively by two agencies within the three-day window, the second rating change is deleted. In line with other studies, we also check the three-day event window to make sure the rating announcement is not contaminated by other informative corporate news. If so, the observation is deleted. Downgrades to default are not part of the sample, as the rating agencies are not bringing new information in these cases.

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[10] In fact, risk-neutral probabilities are higher than actual default probabilities, by an amount that reflects a risk premium (See Berndt et al. (2005)). These results hold, however, as long as a *change* in the actual default probability is reflected in the risk-neutral probability.

[11] The entire sample covers a total of 664 issuers, with 498 issuers with downgrades and 275 issuers with upgrades. On average, an issuer was downgraded 2.5 times during this period, and was upgraded about 1.3 times.

Table 3 displays the distribution of rating downgrades and upgrades by prior rating, using the cardinal scale. The sample has many more downgrades than upgrades, which reflects the downtrend in the average credit rating of U.S. corporations.[12] This asymmetry, however, will decrease the power of tests based on upgrade data. Also, there has not been any instance of upgrade for ratings starting at AA− or above.

[TABLE 3 here]

The bottom panel presents the distribution by rating class. The distribution of prior ratings is not identical across downgrades and upgrades, which may lead to different price effects. For downgrades, 15.56% of the sample is rated below B. This fraction is only 7.48% for upgrades. In fact, when measuring price effects, the comparison should be between a downgrade in a given rating class and an upgrade in the next lower class. Consider for instance, downgrades from B to CCC. The equivalent upgrade is from CCC to B. So, the comparable proportions are 32.47% for downgrades and 7.48% for upgrades. Therefore, the downgrade sample is even more skewed toward a greater proportion of firms with low prior rating.

Table 4 breaks down the sample of rating downgrades by the size of rating changes and by 'within-class' and 'across-class' categories. Most of the rating changes are for one notch only (61.59% of downgrades and 81.16% of upgrades). Downgrades can be more severe than upgrades, however. There are no cases of upgrades of more than four notches, but 6 such cases for downgrades. The average downgrade is for 1.6 notches, versus 1.3 for upgrades. Panel B also reports the distribution of rating changes within each class (e.g., BB to BB−), across class (e.g., BB− to B), and across the investment-grade barrier.

[TABLE 4 here]

[12] Blume et al. (1998) argue that this reflects a tightening of credit standards by rating agencies.

To assess the effect of rating changes on stock returns, we measure the dependent variable as CAR, the cumulative abnormal returns in percentage during the [–1,+1] announcement window for the downgraded firm, where 0 is the effective date of a downgrade:

$$\mathrm{CAR}_j = \sum_{t=-1}^{+1} [R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{jmt})] \tag{6}$$

Abnormal returns are calculated using a market model with parameters estimated over the period $(-250, -50)$ , using the S&P 500 index as the market. In line with previous research, Panel C in Table 4 reports a much stronger average effect for downgrades than for upgrades. This is the puzzle for which this paper provides a structural explanation.

Further, we show that the size of the CAR indeed depends on the prior rating and the absolute magnitude of the rating change. Call the former PRT and the latter RCHG. Table 5 provides preliminary results, classified by prior ratings.

[TABLE 5 here]

The table compares the stock price effect for downgrades and upgrades, matching the prior and final classes and the number of rating changes. For comparison purposes, Panel A reports the unconditional CAR from Table 4. Downgrades are associated with a price change of –4.43%, which is highly significant (t-statistic of –9.95). For upgrades, the "unconditional" price change is only +0.31%, closer to zero. The downgrade effect is 14 times larger than the upgrade effect. The rightmost column tests the null that the magnitude of stock price reactions to downgrades and upgrades is identical, which is strongly rejected. The issue is whether the asymmetry persists conditional on matching the prior and final rating.

Panel B controls for the prior and final class. Differences between downgrades and upgrades are much less than before. These comparisons are still not ideal, however, because the average rating change is larger for downgrades than upgrades. Finally, Panel C provides the cleanest comparison, controlling for both the prior and final classes and the credit rating change. CARs are compared for movements of one notch (RCHG=1) across classes. For example, downgrades from B to "Below B", which has to be necessarily from B– to CCC+, are associated with a price change of –5.04, which is significant. Comparable upgrades, from CCC+ to B– are associated with a return of +2.52, which is also significant. When properly accounting for the prior and final rating, as well as the size of the rating change, upgrades have a non-negligible announcement effect, which is now half that of downgrades. The last column tests the significance of the difference in absolute values. Panel C shows that when adjusting for the size of the change, the difference appears insignificant. So, the absence of announcement effect for upgrades found in previous studies can be in large part explained by this non-linear dependence on the prior and final rating. Panel C of Table 5 provides the cleanest test performed to date of the effect of prior rating.

More generally, previous research provides tests of informativeness of rating changes estimated with a cross-section:[13]

$$\text{CAR}_j = \alpha_0 + \alpha_1 \text{RCHG}_j + \alpha_2 \text{IGRADE}_j + \varepsilon_j \tag{7}$$

The first variable of interest is RCHG, which is the absolute magnitude of the rating change. For downgrades, the sign of the coefficient on RCHG should be negative, implying that a large drop in the credit rating will have a larger stock price effect, and conversely for upgrades. Typically, the regression also examines the effect of IGRADE, which is a dummy variable set to 1 if the rating crosses the investment to speculative-grade border, and to 0 otherwise. It is sometimes argued that there are separate clienteles for investment-grade and speculative-grade bonds, which should lead to

[13] Previous work also tries to account for rating volatility. Some firms have a higher number of rating changes, which may affect the stock price reaction. We added to the regression a variable defined as the natural log of the number of days between two consecutive rating changes of the same bond in the same direction. The variable was insignificant and hence is not included in the analysis.

a larger absolute price response when the border is crossed. This implies that the coefficient for IGRADE should be negative for a downgrade, and conversely for an upgrade. Results are shown in Table 6.

[TABLE 6 here]

The left panel in Table 6 displays results for downgrades. The coefficient on RCHG is significant and negative, as expected. The coefficient on IGRADE is not significant.[14] To account for the prior classification, we add a dummy variable, SGRADE, which takes the value of one if the prior rating is below investment grade. This is strongly significant for both downgrades and upgrades. More insights can be obtained with a cardinal measure of the prior rating, however.

Table 7 augments Equation (7) with the variable PRT, which is the cardinal measure of the prior rating. For downgrades, the PRT coefficient is negative and strongly significant, which indicates that lower prior ratings are associated with larger negative stock price effects.[15] For upgrades, the PRT coefficient is positive and significant, also as expected. Thus the prior rating seems to be an important driver of the stock return, perhaps the single most important one. The IGRADE variable, on the other hand, is insignificant, confirming that there is no investment-grade effect once the prior rating is properly taken into account.

[TABLE 7 here]

We should note that the cross-sectional specification in Table 7 provides a noticeable improvement over traditional models. For downgrades, the R-square improves sharply, from 3.92% for the traditional specification in Table 6 to 8.38% in Table 7.

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[14] Note that this coefficient is significant and negative, as in previous research, when the sample is restricted to investment-grade firms.

[15] The regression forecasts positive returns for downgrades when starting from high credit ratings, which is unexpected. When this is the case, however, the numbers are not statistically significant. This problem is due to forcing the coefficients to be the same, which is alleviated in the following table.

Next, Table 8 presents a finer analysis of the downgrade price effect by classifying bonds into six prior rating classes. We define six dummy variables equal to 1, or 0 otherwise, as DM1 if PRT=1,2,3,4 (for ratings AAA and AA), DM2 if PRT=5,6,7 (for A), DM3 if PRT=8,9,10 (for BBB), DM4 if PRT=11,12,13 (for BB), DM5 if PRT=14,15,16 (for B), and DM6 in other cases. This specification is more flexible than a single slope coefficient on PRT and allows non-linear effects. Indeed the structural model pictured in Figure 1 displays a complex relationship between CAR and PRT.

[TABLE 8 here]

The table focuses first on the effect by class, then on the effect of the size of the rating change, then on both. For ease of interpretation, the models have no intercept. For downgrades, "Model 1" shows a remarkably monotonic relationship between the size of the coefficient and the rating class. Going from the first to the sixth class, the price impact decreases from +4.02% to –6.92%.[16] The F-test in the table confirms that the coefficients on the prior ratings class are significantly different from each other. Once again, the IGRADE variable is insignificant.

Adding an interaction term between the prior rating and the size of the rating change improves the model slightly. "Model 2" uses the interaction between the DM dummy variables and RCHG. The coefficient on DM*RCHG decreases for lower rating classes. "Model 3" uses both the DM dummies and interactions. The R-square increases further, although not when adjusting for degree of freedom, due to the collinearity between DM and RCHG.[17] Also, there is a lack of dispersion in RCHG for some values of DM. Overall, however, the R-square in this panel of Table 8 has substantially increased relative to value of 3.92% in Table 6. It is now above 16%. So, our model brings a substantial improvement to the cross-sectional fit.

[16] The price impact for DM1 is positive due to the other variables in the regression, which shift the intercept up.

The other panel in the table considers upgrades. Because there is no instance of upgrades from AA− or above, DM1 is not included. We also observe a remarkably nearly monotonic effect in the coefficients on the DM variables. Going from the second to the sixth class, the price impact increases from −0.59% to +1.71%, holding other variables fixed. Thus the price effect is more pronounced for lower prior ratings, as predicted, which is confirmed by the F-statistic of equal coefficients. Similar effects appear in the second column, which accounts for the size of the rating change, although the coefficients are not significant, perhaps due to the lack of dispersion in RCHG. The third column is inconclusive and has insignificant F-statistics. [18] Overall, these results confirm the analysis in Table 5, and demonstrate that the prior rating is crucial to understand the stock market response to credit rating changes.

## V. CONCLUSIONS

This paper used a structural credit risk model to demonstrate that the stock price effect of rating changes should depend on the values of the ratings prior and after the announcement. We found that this prediction is strongly confirmed empirically. Holding constant the magnitude of the rating change, the rating prior to the announcement is the single most important variable in cross-sections of stock returns. Lower prior ratings are associated with larger price effects, both for downgrades and upgrades.

Thus, the rapidly expanding literature on the informativeness of rating changes has missed an important explanatory variable in the cross-section. At best, regressions or classifications that omit this effect needlessly reduce their explanatory power. At worst, this may cause errors in

[17] As an example, a regression of RCHG on PRT yields a t-statistic of 8.6. Lower prior ratings are associated with larger changes in credit ratings.

inference if the prior rating is correlated with the variable of interest. For instance, we find that the effect of the investment-grade barrier variable disappears once the prior rating is taken into account.

To illustrate the importance of these results, we reexamined the price impact of downgrades versus upgrades. We confirm that the unconditional price effect of upgrades is barely significant. In our sample, it is 14 times smaller than the effect of downgrades. This result, however, is partly an artifact of the distribution of prior ratings of firms subject to bond upgrades versus downgrades. After correction, the upgrade effect is much greater and strongly significant when starting from a lower credit rating. Contrary to previous research that casts doubt on the informativeness of bond upgrades, our result suggests that upgrades also carry important information value, particularly for firms close to the default threshold. This is a novel result. Compared to downgrades, however, this effect is still smaller, at about half the effect of downgrades when controlling for the prior and final rating. This remaining discrepancy could reflect the fact that companies tend to bias their news releases toward good news, or the fact that rating agencies expend more resources in detecting credit deterioration rather than improvement.

Overall, the theoretical model developed in this paper, which is strongly supported by empirical results, demonstrates the importance of accounting for the prior credit rating in evaluating the informativeness of bond rating changes.

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[18] We also estimated a regression pooling downgrades and upgrades, with the CAR on the latter multiplied by -1, that adjust for the prior rating and the size of the rating change. The results also point to a bigger price effect of downgrades than upgrades, holding all the other variables fixed.

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**Fig.1. Log Stock Value, Credit Rating, and Default Probability**

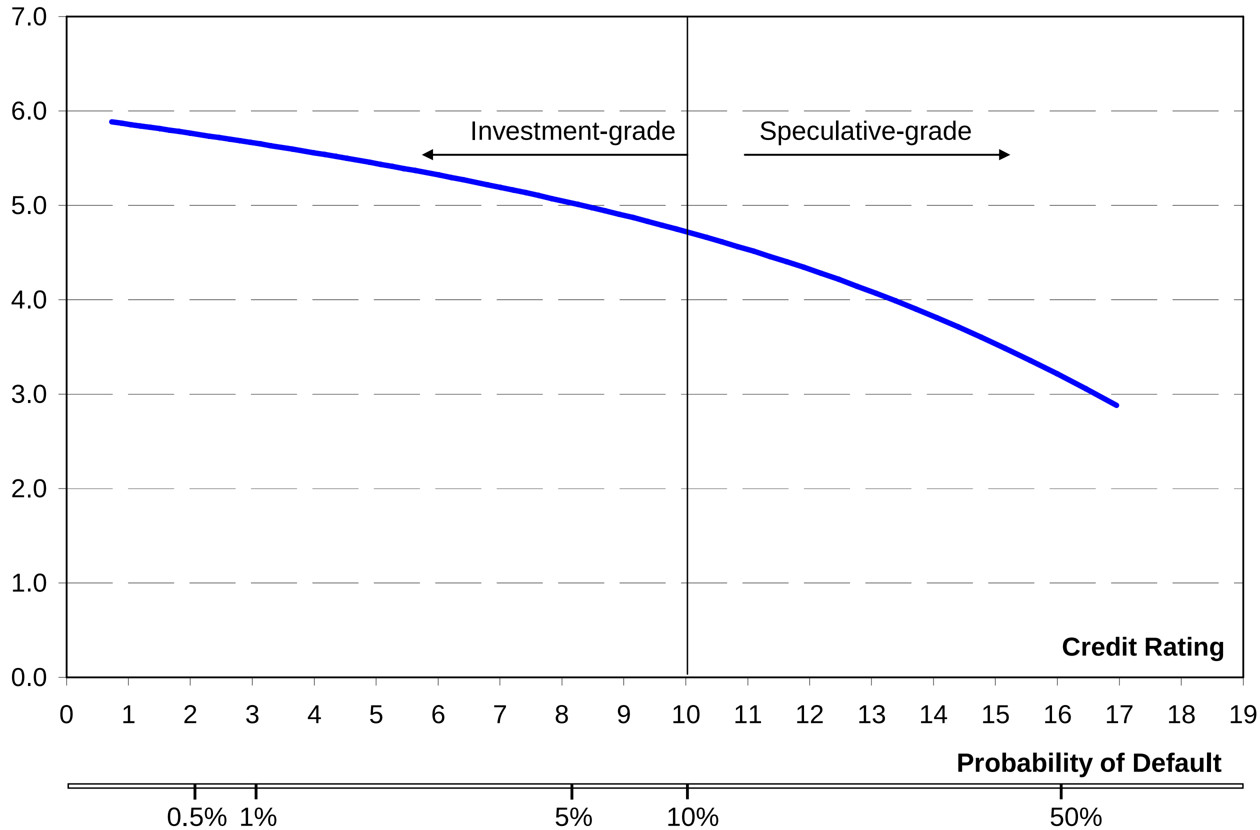

**Table 1. Classification by Credit Ratings**

| Explanation | Standard & Poor's (Modifiers) | Moody's (Modifiers) | Cardinal Scale |
|---|---|---|---|
| **Investment grade:** | | | |
| Highest grade | AAA | Aaa | 1 |
| High grade | AA (+, none,-) | Aa (1,2,3) | 2, 3, 4 |
| Upper medium grade | A (+, none, -) | A (1,2,3) | 5, 6, 7 |
| Medium grade | BBB(+, none,-) | Baa (1,2,3) | 8, 9, 10 |
| **Speculative grade:** | | | |
| Lower medium grade | BB (+, none,-) | Ba (1,2,3) | 11, 12, 13 |
| Speculative | B (+, none,-) | B (1,2,3) | 14, 15, 16 |
| Poor standing | CCC (+, none,-) | Caa (1,2,3) | 17, 18, 19 |
| Highly speculative | CC | Ca | 20 |
| Lowest quality, no interest | C | C | 21 |
| In default | D | | 23 |

**Table 2. Credit Rating and Default Frequency**

**10-Year Horizon, S&P 1981-2002**

| Rating | Scale | Default Frequency | |
|---|---|---|---|
| | | Actual | Fitted |
| AAA | 1 | 0.005 | 0.003 |
| AA+ | 2 | 0.004 | 0.005 |
| AA | 3 | 0.007 | 0.007 |
| AA– | 4 | 0.012 | 0.010 |
| A+ | 5 | 0.016 | 0.015 |
| A | 6 | 0.017 | 0.022 |
| A- | 7 | 0.023 | 0.031 |
| BBB+ | 8 | 0.047 | 0.045 |
| BBB | 9 | 0.055 | 0.065 |
| BBB– | 10 | 0.109 | 0.092 |
| BB+ | 11 | 0.140 | 0.128 |
| BB | 12 | 0.187 | 0.177 |
| BB– | 13 | 0.265 | 0.238 |
| B+ | 14 | 0.315 | 0.313 |
| B | 15 | 0.396 | 0.400 |
| B– | 16 | 0.492 | 0.493 |
| CCC | 17 | 0.572 | 0.586 |

**Table 3**
**Breakdown of Rating Changes by Original Ratings**

Panel A: Distribution by Original Rating before Rating Change Announcements

| Original Rating | Standard & Poor's | Moody's | Downgrades Number | Downgrades % | Upgrades Number | Upgrades % |
|---|---|---|---|---|---|---|
| 1 | AAA | Aaa | 2 | 0.17 | | |
| 2 | AA+ | Aa1 | 4 | 0.33 | | |
| 3 | AA | Aa2 (Aa) | 12 | 1.00 | | |
| 4 | AA- | Aa3 | 28 | 2.34 | | |
| 5 | A+ | A1 | 49 | 4.10 | 5 | 1.39 |
| 6 | A | A2 (A) | 51 | 4.27 | 11 | 3.05 |
| 7 | A- | A3 | 82 | 6.86 | 22 | 6.09 |
| 8 | BBB+ | Baa1 | 82 | 6.86 | 18 | 4.99 |
| 9 | BBB | Baa2 (Baa) | 79 | 6.61 | 26 | 7.20 |
| 10 | BBB- | Baa3 | 77 | 6.44 | 30 | 8.31 |
| 11 | BB+ | Ba1 | 54 | 4.52 | 31 | 8.59 |
| 12 | BB | Ba2 (Ba) | 41 | 3.43 | 21 | 5.82 |
| 13 | BB- | Ba3 | 60 | 5.02 | 45 | 12.47 |
| 14 | B+ | B1 | 95 | 7.95 | 36 | 9.97 |
| 15 | B | B2 (B) | 139 | 11.63 | 45 | 12.47 |
| 16 | B- | B3 | 154 | 12.89 | 44 | 12.19 |
| 17 | CCC+ | Caa1 | 85 | 7.11 | 15 | 4.16 |
| 18 | CCC+ | Caa2 (Caa) | 71 | 5.94 | 6 | 1.66 |
| 19 | CCC- | Caa3 | 21 | 1.76 | 3 | 0.83 |
| 20 | CC | Ca | 9 | 0.75 | 1 | 0.28 |
| 21 | C | C | | | 2 | 0.55 |
| Total | | | 1195 | 100 | 361 | 100.00 |

Panel B: Distribution by Original Rating Class before Rating Change Announcements

| Original Rating Class | Downgrades Starting from | Downgrades Number | Downgrades % | Upgrades Starting fron | Upgrades Number | Upgrades % |
|---|---|---|---|---|---|---|
| 1 | AAA & AA | 46 | 3.85 | | | |
| 2 | A | 182 | 15.23 | A | 38 | 10.53 |
| 3 | BBB | 238 | 19.92 | BBB | 74 | 20.50 |
| 4 | BB | 155 | 12.97 | BB | 97 | 26.87 |
| 5 | B | 388 | 32.47 | B | 125 | 34.63 |
| 6 | Below B | 186 | 15.56 | Below B | 27 | 7.48 |
| Total | | 1195 | 100.00 | | 361 | 100.00 |

Note: The sample consists of 1195 downgrades and 361 upgrades of U.S. corporate bonds (senior unsecured debt) by Standard & Poor's and Moody's during the period of January 1996 to May 2002.

**Table 4**
**Descriptive Statistics of Rating Downgrades and Upgrades**

Panel A: Distribution by absolute magnitude of rating changes

| Absolute magnitude of rating categories changed | Downgrades | | Upgrades | |
|---|---|---|---|---|
| | Number | % | Number | % |
| 1 | 736 | 61.59 | 293 | 81.16 |
| 2 | 304 | 25.44 | 46 | 12.74 |
| 3 | 109 | 9.12 | 18 | 4.99 |
| 4 | 40 | 3.35 | 4 | 1.11 |
| 5 | 4 | 0.33 | | |
| 6 | 2 | 0.17 | | |
| Total | 1195 | 100 | 361 | 100 |
| Mean | 1.6 | | 1.3 | |
| Median | 1.0 | | 1.0 | |

Panel B: Distribution of crossover rating changes

| Rating change | Downgrades | | Upgrades | |
|---|---|---|---|---|
| | Number | % | Number | % |
| Full Sample: Within class | 678 | 56.74 | 226 | 62.60 |
| Across class | 517 | 43.26 | 135 | 37.40 |
| Across Investment Grade | 88 | 7.36 | 42 | 11.63 |
| Total | 1195 | 100 | 361 | 100.00 |

Panel C: Stock Price Response

| | Downgrades | | Upgrades | |
|---|---|---|---|---|
| | CAR | T-stat | CAR | T-stat |
| Abnormal return | -4.43*** | -9.95 | 0.31* | 1.81 |

Notes: Magnitude of rating changes is the cardinal value of new rating minus the cardinal value of old rating. "Across Investment Grade" refer to bonds that are originally rated as investment grade but are downgraded to speculative grade or vice versa; "across class" or "within class" refers to rating changes that move a bond across the rating classes (e.g., BB- to B) or within the same letter class (e.g., BB+,BB,BB-). CAR is the cumulative abnormal returns in percentage for [-1,+1] announcement window for the rating change, where 0 is the effective date of the change. Abnormal returns are calculated using a market model estimated over the period (-250,-50).

***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 5**
**Comparison of Stock Market Response For Downgrades and Upgrades by Class**

Panel A: All Ratings Changes

| S&P Class | | Downgrades | | | Upgrades | | | T-test for Diff |
|---|---|---|---|---|---|---|---|---|
| Lower | Higher | N. | CAR | T-stat | N. | CAR | T-stat | |
| All | All | 1195 | -4.43*** | -9.95 | 361 | 0.31* | 1.81 | 8.66 |

Panel B: RCHG ≥ 1

| S&P Class | | Downgrades | | | Upgrades | | | T-test for Diff |
|---|---|---|---|---|---|---|---|---|
| Lower | Higher | N. | CAR | T-stat | N. | CAR | T-stat | |
| A | Above A | 28 | 0.9 | 1.50 | 5 | -0.24 | -0.10 | 0.39 |
| BBB | A | 100 | -0.31 | -0.46 | 25 | 0.41 | 0.75 | 0.07 |
| BB | BBB | 85 | -2.81*** | -3.32 | 42 | 0.18 | 0.36 | 2.08** |
| B | BB | 83 | -4.08*** | -3.22 | 45 | 1.12** | 2.21 | 2.16** |
| Below B | B | 215 | -8.36*** | -6.94 | 18 | 2.31*** | 3.05 | 4.25*** |

Panel C: RCHG = 1

| S&P Class | | Downgrades | | | Upgrades | | | T-test for Diff |
|---|---|---|---|---|---|---|---|---|
| Lower | Higher | N. | CAR | T-stat | N. | CAR | T-stat | |
| A | Above A | 23 | 0.86 | 1.25 | 5 | -0.24 | -0.10 | 0.34 |
| BBB | A | 56 | -0.66 | -0.60 | 17 | 0.9 | 1.54 | 0.12 |
| BB | BBB | 48 | -2.74*** | -2.32 | 28 | 0.17 | 0.24 | 1.57 |
| B | BB | 39 | -2.87** | -2.05 | 28 | 1.42** | 2.06 | 0.83 |
| Below B | B | 73 | -5.04*** | -3.37 | 14 | 2.52*** | 2.64 | 0.73 |

Notes: The variable of interest is CAR, the cumulative abnormal returns in percentage for [-1,+1] announcement window for the rating change, where 0 is the effective date of the change. Abnormal returns are calculated using a market model estimated over the period (-250,-50) ; RCHG is the absolute magnitude of the rating change, where categorical bond ratings are converted into a cardinal variable measured on a 23 point scale. Panel A reports all CARs. Panel B reports the CAR for all rating changes between two letter classes. Panel C reports the CAR across letter classes with RCHG of 1, e.g. from BB+ to BBB-. For each line, downgrades and upgrades are between the same letter classes. The rightmost column test the null that the stock price reaction to downgrades and upgrades is identical in absolute value across each rating class.
***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 6**
**The Sensitivity of Stock Market Response to the Magnitude of Rating Changes**

| Independent variables | Downgrades | | Upgrades | |
|---|---|---|---|---|
| | Coefficient (t-stat.) | Coefficient (t-stat.) | Coefficient (t-stat.) | Coefficient (t-stat.) |
| Intercept | 0.98 | 3.46*** | 0.10 | -0.42 |
| | (1.06) | (3.40) | (0.26) | (-0.94) |
| RCHG | -3.60*** | -2.92*** | 0.18 | 0.13 |
| | (-6.89) | (-5.52) | (0.63) | (0.46) |
| IGRADE | 2.62 | -1.04 | -0.21 | -0.51 |
| | (1.56) | (-0.58) | (-0.39) | (-0.39) |
| SGRADE | | -5.34*** | | 0.90*** |
| | | (-5.50) | | (2.39) |
| R-squared (%) | 3.92 | 6.30 | 0.13 | 1.71 |
| Adj.R-squared (%) | 3.76 | 6.06 | -0.43 | 0.88 |
| p-value for F-stat. | <.0001 | <.0001 | 0.7933 | 0.1044 |
| Nb. of Obs. | 1195 | 1195 | 361 | 361 |

Notes: The dependent variable is CAR, the cumulative abnormal returns in percentage for [-1,+1] announcement window, where 0 is the effective date of an upgrade. Abnormal returns are calculated using a market model estimated over the period (-250,-50) ; RCHG is the absolute magnitude of the rating change, where categorical bond ratings are converted into a cardinal variable measured on a 23 point scale; IGRADE/SGRADE is a dummy variable equal to 1 if bonds are originally rated as investment/speculative grade but are downgraded to speculative/investment grade, and 0 otherwise.
***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 7**
**The Sensitivity of Stock Market Response to the Magnitude of Rating Changes: Effect of Prior Rating**

| Independent variables | Downgrades | Upgrades |
|---|---|---|
| | Coefficient (t-stat.) | Coefficient (t-stat.) |
| Intercept | 9.24*** | -1.18 |
| | (6.55) | (-1.70) |
| PRT | -0.77*** | 0.11** |
| | (-7.62) | (2.23) |
| RCHG | -2.79*** | 0.08 |
| | (-5.35) | (0.27) |
| IGRADE | 0.53 | -0.05 |
| | (0.32) | (-0.09) |
| R-squared (%) | 8.38 | 1.50 |
| Adj.R-squared (%) | 8.15 | 0.68 |
| p-value for F-stat. | <.0001 | 0.3570 |
| Nb. of Obs. | 1195 | 361 |

Notes: See Table 6 for variables definitions. Here, PRT is the rating prior to the announcement.
***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

## Table 8
## The Sensitivity of Stock Market Response to the Magnitude of Rating Changes: Conditioned by the Pre-announcement Rating Class

| Independent Variables | Dependent Variable: CAR | | | | | |
|---|---|---|---|---|---|---|
| | Downgrades | | | Upgrades | | |
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| | Coefficient (t-stat.) | Coefficient (t-stat.) | Coefficient (t-stat.) | Coefficient (t-stat.) | Coefficient (t-stat.) | Coefficient (t-stat.) |
| PRT | | -0.06 | | | 0.02 | |
| | | (-0.86) | | | (0.76) | |
| RCHG | -2.69*** | | | 0.08 | | |
| | (-5.07) | | | (0.28) | | |
| IGRADE | -0.51 | -2.51 | -2.67 | -0.38 | -0.27 | -0.35 |
| | (-0.26) | (-1.16) | (-1.23) | (-0.58) | (-0.40) | (-0.52) |
| DM1 | 4.02* | | 0.90 | | | |
| | (1.75) | | (0.22) | | | |
| DM2 | 3.50** | | -1.25 | -0.59 | | -6.03* |
| | (2.65) | | (-0.51) | (-1.01) | | (-1.79) |
| DM3 | 2.51* | | -0.89 | -0.24 | | -0.17 |
| | (1.89) | | (-0.43) | (-0.47) | | (-0.18) |
| DM4 | 1.12 | | 0.57 | 0.44 | | 0.56 |
| | (0.77) | | (0.22) | (0.78) | | (0.76) |
| DM5 | -1.41 | | 0.61 | 0.34 | | 0.19 |
| | (-1.22) | | (0.40) | (0.75) | | (0.28) |
| DM6 | -6.92*** | | -2.85 | 1.71** | | 2.13 |
| | (-4.72) | | (-1.08) | (2.33) | | -1.62 |
| DM1*RCHG | | 0.12 | -0.44 | | | |
| | | (0.09) | (-0.18) | | | |
| DM2*RCHG | | 0.23 | 0.73 | | -0.51 | 5.37 |
| | | (0.31) | (0.47) | | (-0.95) | (1.66) |
| DM3*RCHG | | 0.22 | 0.46 | | -0.25 | 0.02 |
| | | (0.23) | (0.30) | | (-0.72) | (0.03) |
| DM4*RCHG | | -1.69** | -2.35 | | 0.11 | -0.01 |
| | | (-2.13) | (-1.58) | | (0.32) | (-0.03) |
| DM5*RCHG | | -3.21*** | -3.92*** | | 0.09 | 0.20 |
| | | (-5.03) | (-4.89) | | (0.23) | (0.40) |
| DM6*RCHG | | -5.67*** | -4.88*** | | 0.73 | -0.23 |
| | | (-7.34) | (-3.76) | | (1.41) | (-0.27) |
| R-squared (%) | 15.49 | 16.45 | 16.53 | 3.80 | 2.97 | 4.60 |
| Adj.R-squared (%) | 14.92 | 15.89 | 15.62 | 1.90 | 1.05 | 1.60 |
| p-value for F-stat. | <0.0001 | <0.0001 | <0.0001 | 0.0547* | 0.1500 | 0.1179 |
| Test of equal coefficients: | | | 23 | | | |
| F value for test: | 10.04*** | | 0.31 | 2.05* | | 1.31 |
| F value for test: | 11.82*** | | 0.34 | 2.54** | | 1.47 |
| F value for test: DM1*RCHG=…=DM6*RCH | | 11.26*** | 6.80*** | | 1.02 | 0.60 |
| F value for test: DM1*RCHG=…=DM6*RCH | | 11.65** | 2.97** | | 1.24 | 0.73 |
| Nb. of Obs. | 1195 | 1195 | 1195 | 361 | 361 | 361 |

Notes: See Tables 6 and 7. Here, DMi*RCHG (i=1,2,...,6) is an interaction term, equal to RCHG multiplied by a dummy variable, which equals to 1 if the pre-announcement rating is in the rating class i, and 0 otherwise, where i=1, if PRT=1,2,3,4; i=2, if PRT=5,6,7; i=3,if PRT=8,9,10; i=4, if PRT=11,12,13; i=5, if PRT=14,15,16; and i=6, otherwise. R-squares are measured around an intercept.
***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.