Non-Linear Effects of Bond Rating Changes

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ABSTRACT

This paper demonstrates the importance of the initial credit rating when assessing the effect of a bond rating change on the company's stock price. First, we provide theoretical support for different price effects as a non-linear function of the initial credit rating, using a structural, Merton-type model linking the change in default probability to the change in the stock price. In particular, rating changes should have much greater effects when starting from a lower initial credit rating. This is strongly verified in the empirical data. Accounting for this non-linearity 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, several studies have 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.[4]

So far, however, extant empirical studies have not focused on the importance of the initial credit 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 initial credit rating, using a structural, Merton-type model linking the change in default probability to the change in the stock price. Second, we

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[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 Standard & Poor's (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.

[4] For instance, Jorion et al. (2005) analyze the effect before and after Regulation FD, which conferred an information advantage to the credit rating agencies.

provide strong empirical evidence that the initial rating is extremely important for predicting the size of the stock price reaction. Our results are also consistent with statistical studies of the rating agencies that report different changes in default probabilities for rating changes, conditioned by initial ratings.

Thus, the initial 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 initial rating.

We show 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. 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.[5] Upgrades are associated with an abnormal return of +0.08 percent, which is not significant. More recent studies,

[5] One problem is that ratings announcements may occur as other major news hit the market, this making the effect more difficult to ascertain. Holthausen and Leftwich (1986) distinguish ratings changes from other news, by separating the sample into "contaminated" observations if there is a concurrent *Wall Street Journal* information release in a four-day window around the rating change. In the case of downgrades across rating classes, they report an abnormal average return of -4.77 percent for contaminated observations, and -0.96 percent for non-contaminated ones. Both numbers, however, are statistically significant.

such as Dichev and Piotroski (2001), indicate that upgrades have recently become statistically significant, although their effect is still smaller than downgrades, typically by a factor of five.[6]

The downgrade effect suggests that ratings agencies provide valuable new information to markets. It is not clear, however, why only negative information is 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. A third hypothesis is that upgrades are more often associated with wealth transfer shocks between stockholders and bondholders, as opposed to good news about cash flows. Wealth transfer shocks such as changes in leverage imply negative correlations between bonds and stocks, which could explain why stock prices do not increase with upgrades. Goh and Ederington (1993), however, find that this is not the case.[7]

Another explanation is the design of the empirical cross-section, which largely ignores the initial value of the rating.[8] 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,

[6] 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.

[7] They classify rating changes by reason for the event. For downgrades, 185 events out of 376 are associated with deteriorating cash flows; 122 to changes (increases) in leverage. For upgrades, 178 events out of 234 are associated with cash flows, and 9 only to changes (decreases) in leverage. Thus there are relatively fewer upgrades due to leverage changes.

[8] Some studies, e.g. Hand et al. (1992), separate the sample into investment-grade and speculative-grade to report summary statistics, but still assume the same intercept in cross-sections. Goh and Ederington (1999) provide empirical

however, represents a much larger increase in the default probability and should have a bigger effect on stock prices. Accordingly, if downgrades more often start from lower initial ratings than upgrades, it is not surprising to observe an overall stronger stock price effects for downgrades. Empirically, we do find that the distribution of initial 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 initial rating. The question is whether these omitted variables can explain the differences between downgrades and upgrades.

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 initial 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 initial rating is an important variable that should always be included in the cross-section.

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.

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evidence on the stock price response by credit rating but do not adjust for the size of the rating change, which we find to

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.

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+, 3 as AA, 4 as AA-, and so on until 23 as the default category.[9]

Table 1. Classification by Credit Ratings

Explanation	Standard & Poor's (Modifiers)	Moody's Service (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

be correlated with the initial rating.

[9] We chose 23 instead of 22 for the default category in line with previous studies. Our sample has few defaults, however, so that the choice of this number is not important.

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.[10] 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 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.

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

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

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

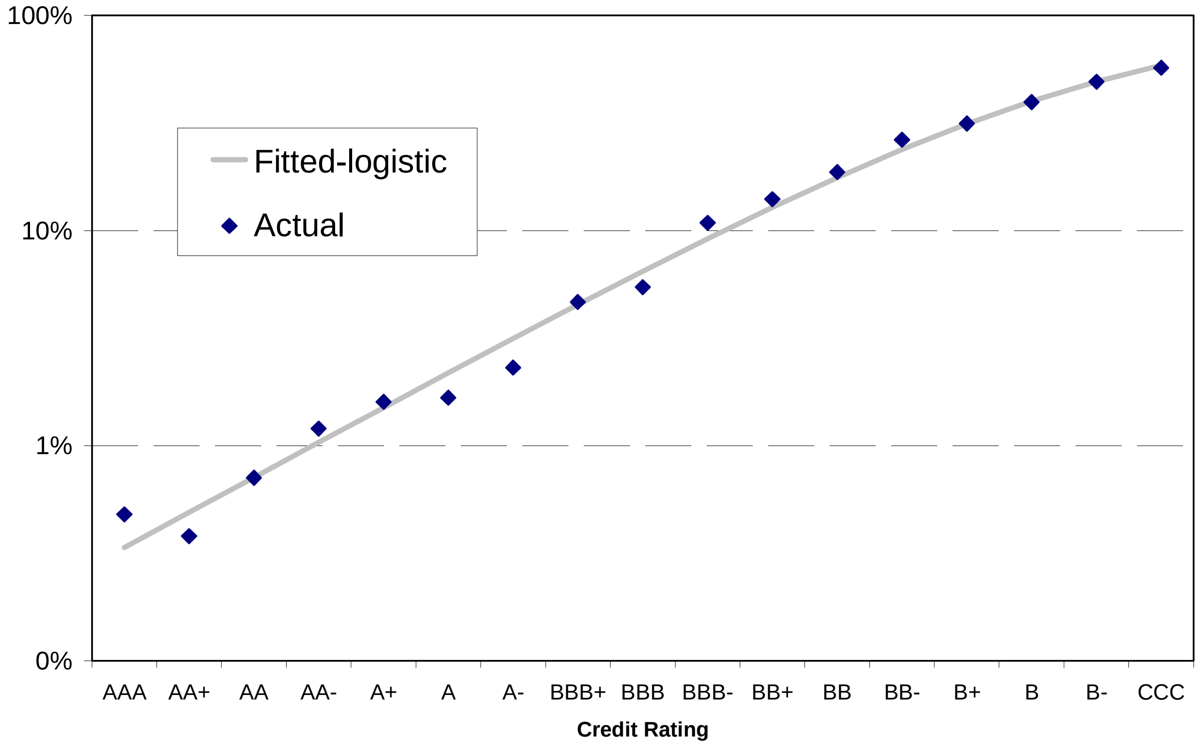
$$\ln\left(\frac{P}{1-P}\right) \equiv y = a + bR + \varepsilon \tag{1}$$

This specification ensures that the resulting probability P is between 0 and 1. The fitted default probabilities are then derived from the estimated equation

$$\ln\left(\frac{\widehat{P}}{1-\widehat{P}}\right) = -6.069 + 0.377R \tag{2}$$

These are shown in the last column of Table 2. Figure 1 displays the actual and fitted default probabilities as a function of the credit rating. The fit is quite good. We shall use the fitted values of default frequencies in what follows.

Fig.1. Actual and Fitted Default Probability: 10-Year S&P



III. STOCK PRICES AND DEFAULT PROBABILITY

The goal of this section is to provide a theoretical basis for the 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.[11] 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.[12]

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

$$dV = V\mu\, dt + V\sigma\, dz \tag{3}$$

[11] 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. Finally, Hui et al. (2003) gives a closed-form solution to a Merton model with a more general boundary.

[12] 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.

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 then 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

$$S = V\ N(d_1) - Ke^{-rT} N(d_2) \tag{4}$$

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:

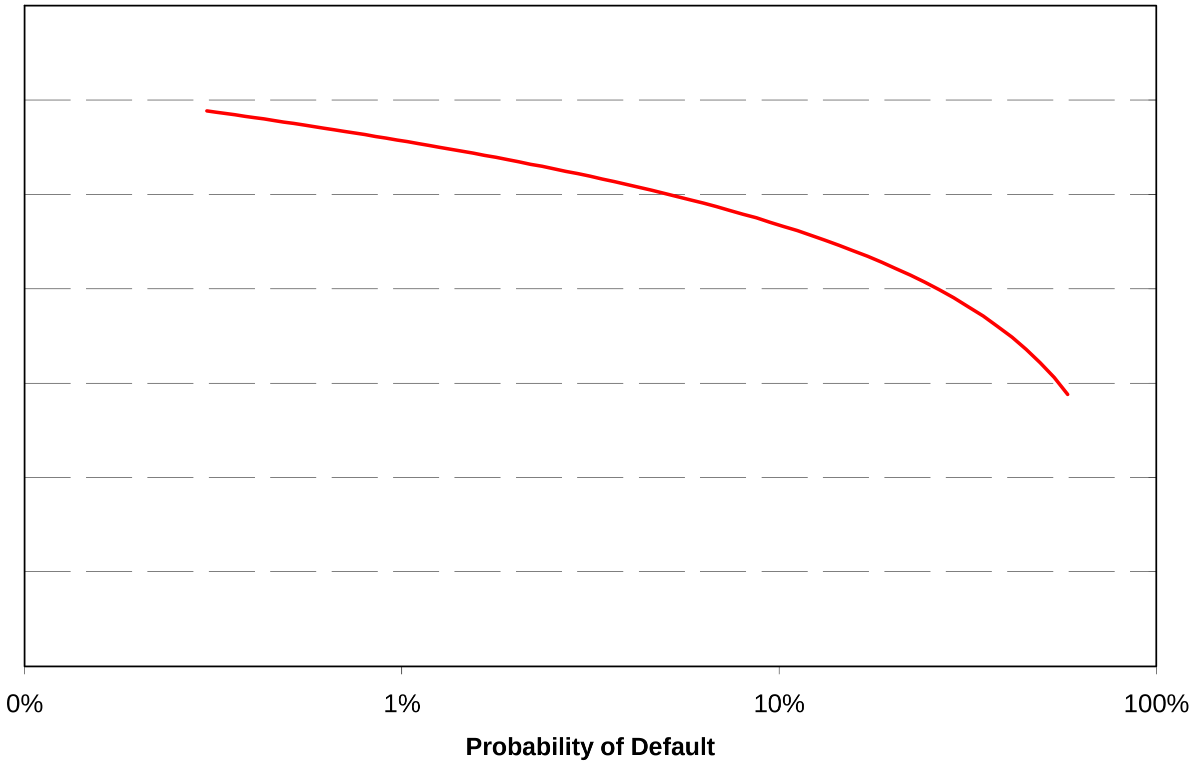
$$P = 1-N(d_2) = N(-d_2) \tag{5}$$

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

$$\frac{d \ln S}{dP} = \frac{1}{S}\frac{\frac{\partial S}{\partial V}}{\frac{\partial P}{\partial V}} = \frac{1}{S}\frac{N(d_1)}{[-\Phi(d_2)/(V\sigma\sqrt{T})]} = -\frac{V}{S}\frac{N(d_1)\sigma\sqrt{T}}{\Phi(d_2)} \tag{6}$$

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 2 using the following parameters: V=\$100, K=\$100, σ=20%, r=5%, T=10 years.

Fig.2. Log Stock Value and Default Probability



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. This gives a relationship between the log of the stock price and the credit rating ln$S$=f(R), which is displayed in Figure 3.

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). Figure 4 displays the slope coefficient. The price impact of a downgrade is multiplied four-fold for an initial rating changing from 1 to 17. Whether this is an important issue is examined next with actual data.

Fig.3. Log Stock Value and Credit Rating

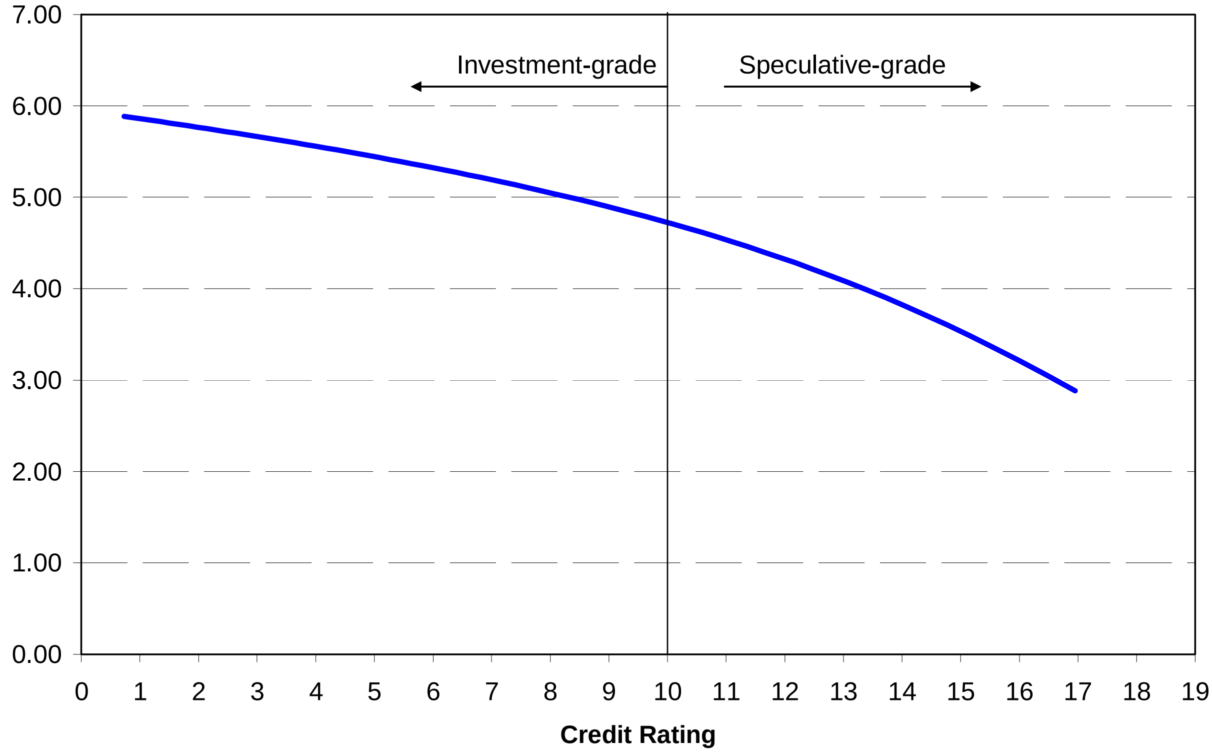
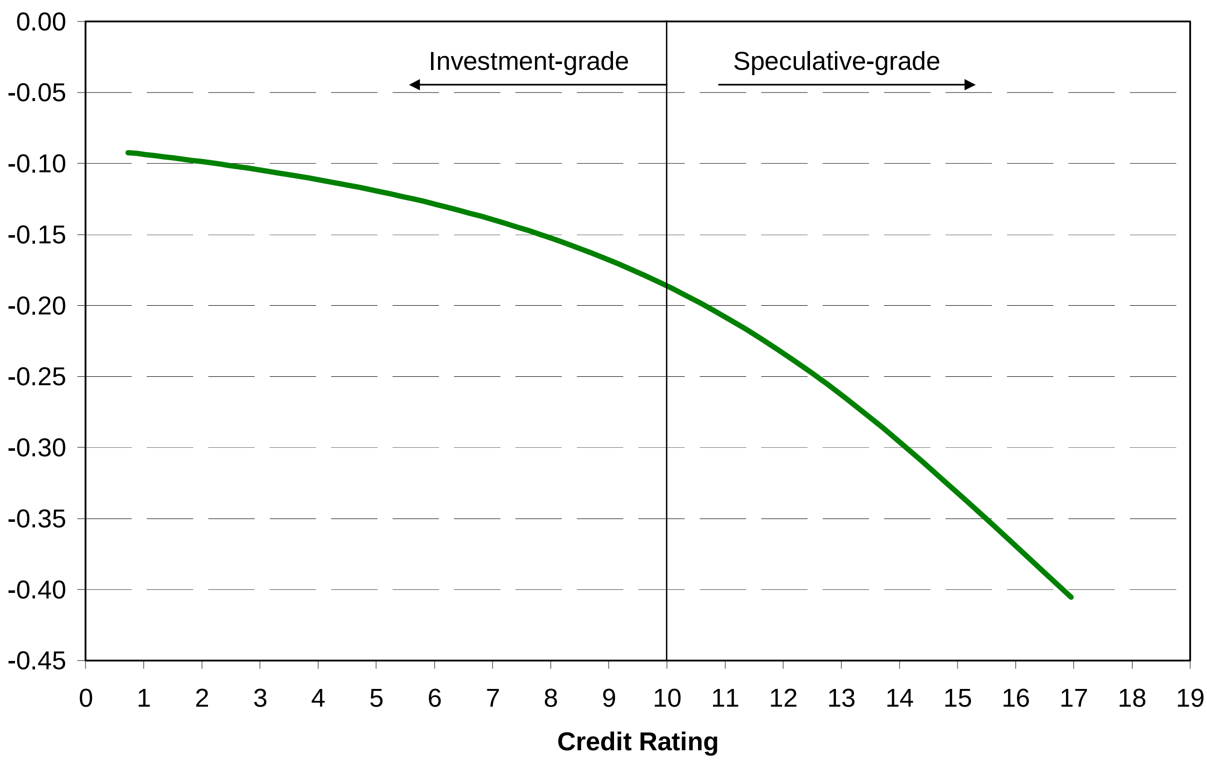


Fig.4. Slope between Log Stock Value and Credit Rating



IV. EMPIRICAL ANALYSIS

Our ratings sample comes from the FISD database. The sample consists of 1229 downgrades and 361 upgrades of corporate bonds by Standard & Poor's and Moody's during the period of January 1995 to May 2002. These are matched with abnormal stock returns in a three-day window around the rating change.

If a rating is changed consecutively by two agencies within the three-day window, the latter 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.

Table 3 displays the distribution of rating downgrades and upgrades by original 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.[13] 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.

The bottom panel presents the distribution by rating class. The distribution of original ratings is not identical across downgrades and upgrades, which may lead to different price effects. For downgrades, 17.66% of the sample is rated below B. This fraction is only 7.48% for upgrades.

[TABLE 3 here]

In fact, for 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 31.81%

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

for downgrades and 7.48% for upgrades. The downgrade sample is even more skewed toward a greater proportion of firms with low initial rating. Taking the average without accounting for this distribution will skew the results.

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 (59.89% of downgrades and 81.16% of upgrades). Downgrades can be more severe than upgrades, however. There are no cases of upgrades for more than four notches, but 14 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]

To assess the effect 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:

$$\mathrm{CAR}_j = \sum_{t=-1}^{+1} [R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{jmt})] \tag{7}$$

Abnormal returns are calculated using a market model with parameters estimated over the period (-250,-50). Panel C reports a much stronger average effect for downgrades than for upgrades, in line with previous research.

Tests of informativeness of rating changes are estimated using:

$$\mathrm{CAR}_j = \alpha_0 + \alpha_1 \mathrm{RCHG}_j + \alpha_2 \mathrm{IGRADE}_j + \varepsilon_j \tag{8}$$

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 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 5.

[TABLE 5 here]

Panel A in Table 5 displays typical results for downgrades. The coefficient on RCHG is significant and negative, as expected, for the whole sample. The coefficient on IGRADE is also negative in the left panel, which is similar to the result found by Holthausen and Leftwich (1986). Superficially, this would support the hypothesis of a clientele effect. This interpretation may not be correct, however, because it may simply reflect the lower initial rating, as most of these bonds are in the BBB category.

In the full sample analysis, this coefficient is actually positive. This could reflect the fact that stock price decreases are less for investment-grade firms. To account for this effect, we add a dummy variable, SGRADE, which takes the value of one if the initial rating is below investment grade. The IGRADE variable becomes insignificant.

In Panel B, for upgrades, none of the coefficients is significant, except for one. This confirms previous work on the ambiguous effect of rating upgrades on stock prices. Also, the investment-grade barrier never seems to matter. The coefficient on SGRADE is significant and positive, however, which points to the importance of the original rating. More insights can be obtained with a cardinal measure of the original rating.

Table 6 augments Equation (8) with the variable ORT, which is the cardinal measure of original rating, prior to the rating change.[14] Panel A, for downgrades, shows that lower initial ratings are associated with bigger negative stock price effects. The effect is strong and significant for speculative-grade issues but not so for investment-grade issues, probably because there is less variation in default probabilities in the investment-grade sample, as predicted by the theory, and because of collinearity with the IGRADE variable.

What matters, however, is the full sample, for which the coefficient on the initial rating variable ORT is negative and strongly significant. The IGRADE variable, on the other hand, becomes insignificant, confirming that there is no investment-grade effect once the initial rating is properly taken into account.

[TABLE 6 here]

Panel B, for upgrades, shows that the ORT coefficient is positive and significant, as expected. In fact, it is the only significant entry in the panel. Thus the initial rating seems to be an important driver of the stock return, perhaps the single most important one.

The cross-sectional specification in Table 6 is a noticeable improvement over traditional models. The R-square has sharply improved, from 6.47% for the traditional specification in Table 5 to 9.97% in Table 6, for downgrades in the full sample. The adjusted R-square also goes up, even after penalizing for the additional degree of freedom.

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

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. "Model 1" in Panel A shows a remarkably monotonic relationship between the size of the coefficient and the rating class. Within the first class (i.e., AAA & AA), a downgrade has a price impact of 4.96%. (Adding the negative effect of RCHG using the median value for this variable gives a net effect of of 4.96%–3.36%×1.6=–0.42%, which is negative). Within the sixth class (i.e., below B), the price effect is -5.03%, which is much more negative than for the first class. The F-test in the table confirms that the coefficients on the original ratings class are significantly different from each other. Once again, the IGRADE variable is insignificant.

Adding an interaction term between the initial 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

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[14] We have not included the SGRADE variable in this regression because it is subsumed by ORT. Even with this added variable, IGRADE is still insignificant.

degree of freedom. This is because of the collinearity between DM and RCHG.[15] Also, there is a lack of dispersion in RCHG for some values of DM. Overall, however, the R-square in this panel of Table 7 has substantially increased relative to value of 6.47% in Table 5. It is now above 17%. The R-square is also higher than that with ORT in Table 6, Panel A, which is 9.97%. So, our model brings a substantial improvement to the cross-sectional fit.

[TABLE 7 here]

Panel B in Table 7 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, which increase as the initial rating decreases. Within the second class (i.e., A), an upgrade has a price impact of -0.59%, to which must be added the effect of RCHG. Next, the effect is +0.24%. Within the sixth class (i.e., below B), the price effect is +1.71%, which is now significant. Thus the price effect is more pronounced for lower initial 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.

One drawback of the previous table is the collinearity between the original rating and the magnitude of the rating change. We adjust for this in Table 8, which compares the stock price effect for downgrades and upgrades, matching the initial and final classes and the number of rating changes. For comparison purposes, Panel A reports the unconditional CAR for downgrades and upgrades from Table 4. In line with previous studies, downgrades are associated with a price

[15] As an example, a regression of RCHG on ORT yields a t-statistic of 8.6. Lower initial ratings are associated with

change of -4.71%, which is highly significant (t-statistic of 10.4). For upgrades, the "unconditional" price change is only 0.31%, close to zero. The downgrade effect is more than 15 times bigger than the upgrade effect. The issue is whether these numbers are the same conditional on matching the initial and final rating.

Panel B controls for the initial and final class. 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 initial 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 initial 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. So, the absence of announcement effect found in previous studies can be in large part explained by this non-linear dependence on the original and final rating. Panel C of Table 8 provides the cleanest test performed to date of the effect of initial rating.[16]

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larger changes in credit ratings.

V. CONCLUSIONS

This paper used a structural credit risk model to demonstrate that the stock price effect of rating changes should depend on the original and final ratings. We found that this prediction is strongly confirmed empirically. Holding constant the magnitude of the rating change, the initial rating is the single most important variable in cross-sections of stock returns. Lower initial 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 inference if the original rating is correlated with the variable of interest. For instance, we find that the effect of the investment-grade barrier variable disappears once the initial 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 15 times smaller than the effect of downgrades. This result, however, is partly an artifact of the distribution of initial 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 initial and final

[16] We also estimated a regression pooling downgrades and upgrades, with the CAR on the latter multiplied by -1, that adjust for the original 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.

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 initial credit rating in evaluating the informativeness of bond rating changes.

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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		Upgrades	
			Number	%	Number	%
1	AAA	Aaa	2	0.16		
2	AA+	Aa1	4	0.33		
3	AA	Aa2 (Aa)	12	0.98		
4	AA-	Aa3	28	2.28		
5	A+	A1	49	3.99	5	1.39
6	A	A2 (A)	51	4.15	11	3.05
7	A-	A3	82	6.67	22	6.09
8	BBB+	Baa1	82	6.67	18	4.99
9	BBB	Baa2 (Baa)	79	6.43	26	7.20
10	BBB-	Baa3	77	6.27	30	8.31
11	BB+	Ba1	54	4.39	31	8.59
12	BB	Ba2 (Ba)	41	3.34	21	5.82
13	BB-	Ba3	60	4.88	45	12.47
14	B+	B1	95	7.73	36	9.97
15	B	B2 (B)	140	11.39	45	12.47
16	B-	B3	156	12.69	44	12.19
17	CCC+	Caa1	88	7.16	15	4.16
18	CCC+	Caa2 (Caa)	73	5.94	6	1.66
19	CCC-	Caa3	27	2.20	3	0.83
20	CC	Ca	16	1.30	1	0.28
21	C	C	13	1.06	2	0.55
Total			1229	100	361	100.00

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

Original Rating Class	Standard & Poor's	Moody's	Downgrades		Upgrades	
			Number	%	Number	%
1	AAA & AA	Aaa & Aa	46	3.74		
2	A	A	182	14.81	38	10.53
3	BBB	Baa	238	19.37	74	20.50
4	BB	Ba	155	12.61	97	26.87
5	B	B	391	31.81	125	34.63
6	Below B	Below B	217	17.66	27	7.48
Total			1229	100	361	100.00

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	59.89	293	81.16
2	317	25.79	46	12.74
3	116	9.44	18	4.99
4	46	3.74	4	1.11
5	5	0.41		
6	6	0.49		
7	2	0.16		
8	1	0.08		
Total	1229	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	581	47.27	224	62.05
Across class	648	52.73	137	37.95
Across Investment Grade	88	7.16	42	11.63
Total	1229	100	361	100.00

Panel C: Stock Price Response

	Downgrades		Upgrades	
	CAR	T-stat	CAR	T-stat
Abnormal return	-4.71***	-10.41	0.31*	1.81

The sample consists of 1229 downgrades and 361 upgrades of corporate bonds by Standard & Poor's and Moody's during the period of 1995 to 2002. 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
The Sensitivity of Stock Market Response to the Magnitude of Rating Changes

Panel A: Downgrade

Independent variables	Investment-grade Subsample	Speculative-grade Subsample	Full Sample	
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Intercept	-0.78	1.41	2.00**	4.41***
	(-1.33)	(1.04)	(2.27)	(4.46)
RCHG	0.43	-4.84***	-4.28***	-3.68***
	(1.08)	(-7.30)	(-9.12)	(-7.67)
IGRADE	-2.71***		2.81*	-0.67
	(-3.73)		(1.65)	(-0.37)
SGRADE				-5.06***
				(-5.13)
R-squared (%)	2.92	6.55	6.47	8.44
Adj.R-squared (%)	2.50	6.42	6.32	8.21
p-value for F-stat.	0.0011	<.0001	<.0001	<.0001
Nb. of Obs.	466	763	1229	1229

Table 5
The Sensitivity of Stock Market Response to the Magnitude of Rating Changes

Panel B: Upgrade

Independent variables	Investment-grade Subsample	Speculative-grade Subsample	Full Sample	
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Intercept	-0.65	0.53	0.10	-0.42
	(-0.94)	(1.10)	(0.26)	(-0.94)
RCHG	0.33	0.09	0.18	0.13
	(0.60)	(0.25)	(0.63)	(0.46)
IGRADE		-0.49	-0.21	-0.51
		(-0.83)	(-0.39)	(-0.39)
SGRADE				0.90***
				(2.39)
R-squared (%)	0.32	0.28	0.13	1.71
Adj.R-squared (%)	-0.59	-0.53	-0.43	0.88
p-value for F-stat.	0.5529	0.7065	0.7933	0.1044
Nb. of Obs.	112	249	361	361

Variable definitions:
The dependent variable is CAR, the cumulative abnormal returns in percentage for [-1,+1] announcement window, where 0 is the effective date of the rating 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; IGRADE is a dummy variable equal to 1 if bonds are originally rated as investment grade but are downgraded to speculative grade or vice versa, and 0 otherwise; SGRADE is a dummy variable equal to 1 for bonds originally rated as speculative grade.
***, **, * 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: Effect of Original Rating

Panel A: Downgrade

Independent variables	Investment-grade Subsample	Speculative-grade Subsample	Full Sample
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Intercept	0.17	17.92***	9.39***
	(0.12)	(3.92)	(6.83)
ORT	-0.13	-1.12***	-0.70***
	(-0.73)	(-3.78)	(-6.90)
RCHG	0.36	-4.43***	-3.47***
	(0.87)	(-6.66)	(-7.30)
IGRADE	-2.29***		0.81
	(-2.45)		(0.48)
R-squared (%)	3.03	8.27	9.97
Adj.R-squared (%)	2.40	8.03	9.75
p-value for F-stat.	0.0026	<.0001	<.0001
Nb. of Obs.	466	763	1229

Table 6
The Sensitivity of Stock Market Response to the Magnitude of Rating Changes: Effect of Original Rating

Panel B: Upgrade

Independent variables	Investment-grade Subsample	Speculative-grade Subsample	Full Sample
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Intercept	-0.75	0.06	-1.18
	(-0.52)	(0.03)	(-1.70)
ORT	0.01	0.03	0.11**
	(0.08)	(0.26)	(2.23)
RCHG	0.32	0.07	0.08
	(0.56)	(0.20)	(0.27)
IGRADE		-0.37	-0.05
		(-0.49)	(-0.09)
R-squared (%)	0.33	0.31	1.50
Adj.R-squared (%)	-1.50	-0.91	0.68
p-value for F-stat.	0.8366	0.8589	0.3570
Nb. of Obs.	112	249	361

Variable definitions:

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; ORT is the rating prior to the rating change announcement; IGRADE is a dummy variable equal to 1 if bonds are originally rated as investment grade but are downgraded to speculative grade or vice versa, 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: Conditioned by the Pre-announcement Rating Class

Panel A: Downgrade

Independent Variables	Model 1	Model 2 (Dependent Variable CAR)	Model 3
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
ORT		0.01	
		(0.07)	
RCHG	-3.36***		
	(-6.95)		
IGRADE	-0.06	-2.58	-2.67
	(-0.03)	(-1.17)	(-1.21)
DM1	4.96**		0.90
	(2.13)		(0.22)
DM2	4.43***		-1.25
	(3.40)		(-0.50)
DM3	3.23***		-0.89
	(2.43)		(-0.42)
DM4	2.18		0.57
	(1.52)		(0.21)
DM5	-0.42		1.50
	(-0.38)		(1.05)
DM6	-5.03***		-1.37
	(-3.53)		(-0.60)
DM1*RCHG		0.01	-0.44
		(0.01)	(-0.18)
DM2*RCHG		-0.01	0.73
		(-0.01)	(0.46)
DM3*RCHG		-0.12	0.46
		(-0.12)	(0.29)
DM4*RCHG		-2.09***	-2.35
		(-2.64)	(-1.55)
DM5*RCHG		-3.89***	-4.50***
		(-6.73)	(-6.25)
DM6*RCHG		-5.71***	-5.14***
		(-8.84)	(-5.18)
R-squared (%)	17.43	18.62	18.75
Adj.R-squared (%)	16.89	18.09	17.88
p-value for F-stat.	<0.0001	<0.0001	<0.0001
Test of equal coefficients:			
F value for test: DM1=DM2=…=DM6=0	9.20***		0.33
F value for test: DM1=DM2=…=DM6	9.97***		0.39
F value for test: DM1*RCHG=DM2*RCHG=…=DM6*RCHG=0		16.10***	11.46***
F value for test: DM1*RCHG=DM2*RCHG=…=DM6*RCHG		13.50***	3.97***
Nb. of Obs.	1229	1229	1229

Table 7

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

Panel B: Upgrade

Independent Variables	Model 1	Model 2	Model 3
		Dependent Variable CAR	
	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
ORT		0.02	
		(0.76)	
RCHG	0.08		
	(0.28)		
IGRADE	-0.38	-0.27	-0.35
	(-0.58)	(-0.40)	(-0.52)
DM2	-0.59		-6.03*
	(-1.01)		(-1.79)
DM3	-0.24		-0.17
	(-0.47)		(-0.18)
DM4	0.44		0.56
	(0.78)		(0.76)
DM5	0.34		0.19
	(0.75)		(0.28)
DM6	1.71**		2.13
	(2.33)		(1.62)
DM2*RCHG		-0.51	5.37
		(-0.95)	(1.66)
DM3*RCHG		-0.25	0.02
		(-0.72)	(0.03)
DM4*RCHG		0.11	-0.01
		(0.32)	(-0.03)
DM5*RCHG		0.09	0.20
		(0.23)	(0.40)
DM6*RCHG		0.73	-0.23
		(1.41)	(-0.27)
R-squared (%)	3.80	2.97	4.60
Adj.R-squared (%)	1.90	1.05	1.60
p-value for F-stat.	0.0547*	0.1500	0.1179
Test of equal coefficients:			
F value for test: DM2=…=DM6=0	2.05*		1.31
F value for test: DM2=…=DM6	2.54**		1.47
F value for test: DM2*RCHG=…=DM6*RCHG=0		1.02	0.60
F value for test: DM2*RCHG=…=DM6*RCHG		1.24	0.73
Nb. of Obs.	361	361	361

Variable definitions:

The dependent variable 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; ORT is the rating prior to announcement; 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 ORT=1,2,3,4; i=2, if ORT=5,6,7; i=3,if ORT=8,9,10; i=4, if ORT=11,12,13; i=5, if ORT=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.

Table 8
Comparison of Stock Market Response For Downgrades and Upgrades by Class

Panel A: All Ratings Changes

S&P Class		Downgrades			Upgrades		
Lower	Higher	Number	CAR	T-stat	Number	CAR	T-stat
All	All	1229	-4.71***	-10.41	361	0.31*	1.81

Panel B: RCHG ≥ 1

S&P Class		Downgrades			Upgrades		
Lower	Higher	Number	CAR	T-stat	Number	CAR	T-stat
A	Above A	28	0.9	1.50	5	-0.24	-0.10
BBB	A	100	-0.31	-0.46	25	0.41	0.75
BB	BBB	85	-2.81***	-3.32	42	0.18	0.36
B	BB	83	-4.08***	-3.22	45	1.12**	2.21
Below B	B	218	-8.81***	-7.12	18	2.31***	3.05

Panel C: RCHG = 1

S&P Class		Downgrades			Upgrades		
Lower	Higher	Number	CAR	T-stat	Number	CAR	T-stat
A	Above A	23	0.86	1.25	5	-0.24	-0.10
BBB	A	56	-0.66	-0.60	17	0.9	1.54
BB	BBB	48	-2.74***	-2.32	28	0.17	0.24
B	BB	39	-2.87**	-2.05	28	1.42**	2.06
Below B	B	73	-5.04***	-3.37	14	2.52***	2.64

Variable definitions:
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 the CAR across letter classes with RCHG of 1, e.g. from BB+ to BBB-. Panel B reports the CAR for all rating changes between two letter classes. For each line, downgrades and upgrades are between the same letter classes.
***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.