Tightening Credit Standards: Fact or Fiction?

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ABSTRACT

Over the latest twenty years, the average credit rating of U.S. corporations has trended down. This observation has been interpreted as evidence that rating agencies have been tightening credit standards. More formally, Blume et al. (1998) model the credit rating process by an ordered probit regression and indeed find that the annual intercept, reflecting the average credit rating, has been drifting down, holding the effect of other variables constant. We extend the analysis in several ways. First, we find that this trend does not apply to speculative-grade issuers. Second, we account for structural shifts in investment-grade issuers that could rationally explain this decrease in ratings. Explanations include a shift away from utilities, which are generally less risky than other industries, increasing volatility of market values, and increased manipulation of accounting data. We find that the informativeness of accounting data decreased and that earnings management increased for investment-grade firms, but not for speculative-grade firms. After accounting for all of these effects, we find that the intercept remains stable for both samples, thus providing no support for the view that rating agencies have tightened their credit standards.

JEL Classifications: G14-Information and Market Efficiency, G32-Financing Policy

Keywords: credit rating agencies, credit standards, accounting information, credit risk

I. INTRODUCTION

The importance of credit rating agencies has grown considerably in recent years. Standard and Poor's (S&P) corporation, for instance, states that it "now rates more than $11 trillion in bonds and other financial obligations of obligors in more than 50 countries."[1] In the United States, S&P rates all public corporate debt issues over $50 million—with or without a request from the issuer. Moody's Investor Service states that its ratings now track more than $30 trillion of debt globally.

Credit ratings are important for various types of market participants. Issuers use them to improve the marketability and pricing of their debt.[2] Investors, consisting primarily of buy-side firms, such as mutual funds, pension funds and insurance companies, use them to assess credit risk and to comply with investment guidelines or regulations.[3] Sell-side firms like broker-dealers use them to determine the amount of collateral to hold against derivatives credit exposure. Ratings can also be used in private contracts.[4] Finally, credit ratings are widely used by regulators, especially since the Securities and Exchange Commission (SEC) adopted the designation of Nationally Recognized Statistical Rating Organization (NRSRO) in 1975.[5] This designation, which now includes three agencies, is referenced by at least 8 federal statutes, 47 federal regulations, and over 100 state laws and regulations (Covitz and Harrison, 2003).

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[1] S&P (2003).
[2] In the U.S. corporate debt market, issuers usually obtain ratings from two rating agencies. A single-rated debt may receive a less favorable price than an otherwise equivalent debt with two similar ratings, as the absence of a second rating is usually viewed by investors as the issuer's inability to secure another comparable rating.
[3] For example, bond fund managers may use credit ratings to comply with internal by-law restrictions or investment policies that require certain minimum credit ratings for investments.
[4] Financial contracts can include "ratings triggers," which specify that counterparties can demand more collateral, or request loan repayment, if the credit rating of the counterparty falls below some level. In the case of Enron, for example, ratings triggers were included in trading contracts and contributed to the fast demise of the company.
[5] See the description of the role of credit rating agencies by the SEC (2003).

An issuer rating is an opinion of the obligor's likelihood of default. To be meaningful, the credit rating process should provide ratings that are stable across time and consistent across issuers. Consider for example the Net Capital Rule, which requires broker-dealers to maintain a minimum amount of capital on their balance sheet. The SEC determined that securities with a higher credit rating require lower capital. Drifts in the credit rating process would imply changes in these capital requirements. Another important application is the capital charge for the credit risk of assets such as loans and bonds held by commercial banks.[6] The Basel Committee on Banking Supervision (BCBS) recently instituted new rules that map each credit rating onto a capital charge. For instance, BBB or BB-rated debt will carry an 8% capital charge, versus 4% only for A-rated debt, and 1.6% for AAA or AA-rated debt. These rules require consistency in the application of credit ratings.

Changing probabilities would distort the effectiveness of credit ratings. Suppose, for instance that a bank carries $100 million in an A-rated loan, which is initially calibrated to a capital charge of 4%, or $4 million. Now, if rating agencies tighten credit standards, downgrading the debt to BBB/BB without change in the default probability, the bank would see its capital charge increase from 4% to 8%, by $4 million in this case. If the Basel charges were initially binding, the bank would be forced to raise more capital, or cut lending, without any fundamental change in the risk of its loan portfolio. Such tightening of credit standards will create severe distortions in capital requirements.

In recent years, rating agencies have issued proportionately more downgrades than upgrades. The fraction of lower-rated credit, existing or new, has also increased. This result holds whether we consider the total sample of rated U.S. corporations, which has increased over time, or a fixed sample. For instance, for a constant sample of 137 investment-grade firms for

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[6] See the Basel 2 rules finalized in BCBS (2004).

the period of 1985 to 2002, we find that the average rating fell from A+ to A-, which is a significant shift.

This decrease in average credit ratings could be interpreted as indicative of a *decline in the actual credit quality* of U.S. corporate debt over time, in other words a higher default probability. Another interpretation is that the decline in average ratings reflects *a tightening of credit standards* by agencies, implying changing default probability for a given credit rating. This second explanation is very troublesome, because it would distort the use of credit ratings by market participants.

The problem is that these two competing explanations are difficult to disentangle. Blume, Lim, and MacKinlay (1998) point out that any analysis of the credit rating process should control for risk variables. Examining investment-grade ratings over the period 1978 to 1995, they model credit ratings with a number of accounting and market variables. The annual intercept is then interpreted as a general measure of credit standards, after controlling for the other variables. Interestingly, they report a downward trend in the annual intercept, which is interpreted as systematic tightening of ratings standards, ceteris paribus. If so, the probability of default should decrease over time for a given rating.

This paper re-examines the causes of the observed decrease in average credit ratings. We first examine trends in default rates within each rating category. This provides a preliminary test of whether rating standards have indeed changed over time. We find no evidence that default rates have changed over time, which contradicts the hypothesis of tightening credit standards. Such tests, however, lack power due to the limited number of defaults.

Next, we replicate the results of Blume et al. on our dataset covering the period from 1985 to 2002 and find that the results are confirmed in our sample. We also extend the sample from investment-grade debt only to speculative-grade debt and find no evidence of a downward trend in the intercept for speculative-grade debt. This finding is new and important. However, it conflicts with the tightening explanation, as it is not clear why rating agencies would tighten standards for investment-grade debt but not speculative-grade debt.

We then search for additional structural explanations for the downward drift in the intercept reported by Blume et al. As they recognize, their results should be interpreted as evidence of tightening of credit standards "in terms of the explanatory variables used in the analysis". There is always a possibility that some critical rating factor displaying a downward time trend is missing in their rating models.

One such example is the *increased risk* of U.S. corporations. Campbell et al. (2001) report that the volatility of U.S. stock prices has increased over time. Structural models of the capital structure, such as developed in Merton (1974), predict that default probability is higher when leverage is higher, when the firm value is lower but also when the firm volatility, and hence stock volatility is higher. Thus this increased volatility could predict higher default probability, justifying lower credit ratings. Another explanation is the changing *industry composition* of corporate debt. Some industries are inherently more stable than others, all else equal. An increasing fraction of relatively risky industries could justify lower aggregate credit ratings.

Blume et al. also note the possibility that "the informational content of a specific variable itself has changed over time." *Accounting data* may have become less reliable over time, due to increased earnings management or manipulation. Indeed, Brown, Lo, and Lys (1999) document a decrease in the value relevance of accounting information. Cohen, Dey, and Lys (2004) document a steady increase in earnings management over the period 1987 to 2003, which they attribute to the growing managerial opportunistic behavior as a result of the increasing use of executive stock options. The manipulation of accounting data can take the form of upward bias in reported income, artificial smoothing of earnings, or lower reported leverage. Income can be manipulated upward through discretionary accounting adjustments such as underestimating bad debt expenses and overstating sales revenues.[7] Income can also be smoothed, which makes the firm appear less risky than it really is. Leverage can be decreased through the accounting treatment of operating leases, or by hiding debt in Special Purpose Vehicles that enable the firm to keep debt off its balance sheet, as was the case with Enron. Such manipulation is presumably intended to help the firm appear less risky. In a recent survey by Graham, Harvey, and Rajgopal (2004), financial executives state that they try to meet earnings benchmarks for a number of reasons, including to "achieve or preserve a desired credit rating." This is especially the case for firms that are large and have a high credit rating, which correspond to our investment-grade sample.

Further, recent studies on accounting disclosure and the cost of debt show that firms with lower quality of accounting information are associated with higher perceived default risk and lower credit ratings (e.g., Sengupta, 1998; Yu, 2005). Thus, the observed downward drift in the annual intercept of the credit ratings model may simply represent a rational reaction by the credit rating agencies to the declining quality of accounting information they use to generate their opinion. The agencies mention that "accounting quality" is an issue and do state that "*analytical adjustments are made to better portray reality.*"[8] As a result of the recent accounting scandals

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[7] For example, software companies have been long known for their aggressive revenue recognition practices, e.g., recognizing revenue from software licenses upon signing rather than on delivery for product sales, and recording product maintenance revenue at the inception of the maintenance agreement rather than over the maintenance period.

[8] S&P Corporate Ratings Criteria (2003), p. 22.

such as Enron and WorldCom, rating agencies have started to publish the methodologies they use to filter corporate earnings.[9] The issue is whether the apparent tightening of credit standards can be explained by the reduced information content of accounting variables and increased earnings management.

This paper contributes to the credit ratings literature in several ways. First, we find that the apparent tightening of credit rating is rationally explained by several factors. Second, we document notable differences in the stability of the credit rating process for investment-grade and speculative-grade firms that we trace to differences in the value relevance of accounting data and in earnings management for these two groups. These findings, therefore, enhance our understanding of the credit rating process. Finally, we also contribute to the value-relevance/earnings management literature in accounting by being the first study performing a temporal analysis of the value-relevance of accounting data in assessing credit risk[10] and documenting differential earnings management time trends between the investment-grade and speculative-grade samples.

The remainder of the paper is organized as follows. Section II focuses directly on trends in default rates within each rating category. This provides a preliminary test of whether rating standards have changed over time. We need, however, a more detailed modeling of the rating process. Section III describes data and descriptive statistics for this model. Section IV presents empirical results and alternative explanations. Section V concludes.

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[9] One such example is the "core earnings" measure published by S&P (2002). The company states that "over the last decade… many members of the investment community expressed concern that earnings reports are becoming harder to understand, more difficult to compare across companies, and less useful to analyst and investors."

[10] A recent survey paper on the accounting value-relevance studies by Holthausen and Watts (2001) note that this vast literature has predominantly focused on the value-relevance to *equity* valuation. They argue (p. 26) that "What is relevant for one user or user group, may not be relevant for another. This creates a problem in drawing inferences based on value-relevance research that uses equity values only."

II. TRENDS IN DEFAULT RATES

An issuer rating indicates the obligor's likelihood of default. Rating agencies claim that their ratings provide a consistent framework for comparing credit quality across firms and across time. Indeed, Moody's states that "we generally expect that future default rate experience, measured over a suitably long period of time, will be similar for bonds that carry the same rating."[11] "Consistency" is a recurring key word in descriptions of rating scales. It implies stability in the rating process, and rules out tightening of credit standards.

This section examines the stability of the credit ratings process by focusing on the annual default rate within each rating category. Tightening credit standards imply that default rates should trend down over time, ceteris paribus.

Table 1 presents one-year default rates within a rating class over the next year, as compiled by Standard and Poor's (2004) over the period 1981 to 2003 for global corporations, including non-U.S. firms. This is the longest period for which S&P provides such data.

Each entry represents the annual default rate in percent and is accompanied by its standard error. Take for example the 1981 entry for B-rated bonds. The default rate was 2.27%, out of 88 B-rated bonds at the beginning of the year. This translates into a standard error of 1.59%, from the binomial distribution.

The table shows many zero entries, implying no default within the ratings class. For instance, there has not been any instance of default of AAA-rated bond over these 23 years, or 3,511 firm-years. This is unfortunate (for the econometrician), because it makes it difficult to estimate the probability of default and trends in ratings standards. For AA-rated bonds, we have

[11] Moody's (2001). Ammer and Packer (2000), for example, check for consistency in default rates across sectors and obligor domiciles.

one occurrence of default, out of 603 bonds in 1999.[12] Over the whole sample, this translates into a 0.01% default probability, which is subject to substantial estimation error. A-rated bonds also had very low default rates.

Among investment-grade bonds, BBB bonds have an average default rate of 0.31% over this period. This represents 43 defaults out of 13,870 firm-years. Because of the large sample and number of defaults, the average default rate is estimated more accurately. The standard error is 0.05%, implying that we can be fairly confident that the default rate is not zero.[13] Therefore, we will only be able to identify trends in default rates for the BBB category among investment grade bonds. Likewise, the BB and B categories lead to accurate measures of default rates, because of higher default rates. The CCC/C category, in contrast, has less accurate estimates due to the small sample of bonds.

We can now examine trends in the rating standards. Tightening standards implies that default rates should decrease over time. However, default rates do change over time as a function of economic conditions. Defaults increase during recessions and decrease during expansions. So, it is important to examine a long period that covers various economic conditions.

The lower part of the table compares two subperiods, 1985-1993 and 1994-2002, that cover the sample period in our subsequent analysis. Both periods include a recession. As indicated by "equality t-tests," there is no evidence that default rates are lower in the second subperiod. Instead, default rates are slightly higher in latter years, although not significantly so.

[12] This was General American Life Insurance, which defaulted in August 1999 on $6.8 billion in funding agreements. The company had issued this short-term debt with a 7-day put option. In July 1999, Moody's downgraded the company as a result of deteriorating financial condition. As a result of the downgrade, holders of the funding agreements exercised their puts, triggering a liquidity crisis. This story illustrates how a financial institution can jump from an AA-rating to default within one year.

The last line reports the result of a regression of the annual default rate on a time trend. Results are meaningful only for the A-rated category or below. The "slope t-tests" test whether the slope coefficient is significantly different from zero. All the t-statistics but one are positive, implying an increase in default rate, although not significant.

The conclusion from this section is that there is no evidence of tightening credit standards. Default rates appear to have been fairly constant across time, within each rating category. Admittedly, this is a fairly weak test due to the small number of defaults, especially for high-quality bonds. The next sections provide a structural explanation for apparent changes in the credit rating process observed by Blume et al.

III. DATA AND DESCRIPTIVE STATISTICS

The data uses credit rating information provided by Standard and Poor's (S&P). S&P provides issuer credit ratings for long-term debt. These ratings represent an opinion of an obligor's overall financial capacity (its creditworthiness) to pay its financial obligations.

Our sample starts with the selection of all U.S. firms in the 2002 annual Compustat data that have S&P long-term issuer credit rating (data item 280) at fiscal yearend.[14] Companies also need to have the required accounting variables to construct four accounting ratios used in credit rating models from 1985 to 2002, which is the longest sample period available.[15] The accounting ratios include interest coverage, operating margin, long-term debt leverage, and total

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[13] This is measured as $\sigma = \sqrt{p(1-p)/N}$, where p is the default probability, and N is the number of observations. The usual t-test is based on an asymptotic normal distribution.

[14] The sample consists of both active and inactive firms as of 2002.

[15] Compustat uses its own convention for classifying fiscal years. A firm with its fiscal yearend before June is assigned with a fiscal year equal to calendar year minus one and fiscal year is equal to calendar year if the fiscal yearend is June or later. For example, if firm A's fiscal yearend is May (June or July), the fiscal year ending in May 1991 is classified as 1990 (91) in Compustat. The year variable in our analyses is calendar year.

debt leverage.[16] As in Blume et al., we use three-year averages of these ratios in our analysis. In addition, a firm must also have at least 200 daily stock returns each year from CRSP to estimate the betas and standard errors from the market model. To adjust for nonsynchronous trading effects, we adopt the Dimson (1979) procedure with one leading and lagging value of the CRSP value-weighted market return. The final sample consists of 16,091 firm years with 9,927 investment grade ratings and 6,164 speculative grade ratings. Investment-grade firms are much larger than speculative-grade firms, on average nine times the size in terms of market value.

Table 2 describes the sample by year and credit rating class. Over the 18 years in our sample, the average rating has steadily decreased. The fraction of AA issuers has dropped from 18% to 3%. The decrease in the fraction of AA- and A-rated has been offset by an increase in the fraction of BBB and BB issuers. Across ratings groups, the fraction of investment-grade issuers has also dropped from 74% to 54%. This could be interpreted as a general decrease in the credit quality of U.S. issuers, or tightening of credit standards.

It is interesting to note, however, that the number of rated obligors has also increased steadily during this period. Assuming there was a bias toward high-rated companies at the beginning of the sample, the decrease in average rating could simply reflect the expanding pool of obligors.

Next, Table 3 displays the distribution of ratings by industry and year. The table shows a sharp increase in the proportion of financials among investment-grade firms, associated with a decrease in the proportion of utilities. The fraction went from 7% to 15% over this period. This structural shift is not observed among speculative-grade issuers, however. Normally, agencies

[16] Interest coverage is the ratio of operating income after depreciation plus interest expense to interest expense. Operating margin is the ratio of operating income before depreciation to net sales. LT debt leverage is the ratio of long-term debt to total assets. Total debt leverage is the ratio of total debt to total assets.

take into account differences across industries to assign credit ratings. For instance, a BBB rating is associated with an average debt-to-capital ratio of 42% for industrials versus 59% for utilities. Because utilities can have higher leverage for the same rating, the agencies must view utilities are safer than industrials for the same financial ratio. Conversely, financials are less safe than industrials. Perhaps the tightening of credit standards is due in part to the increased proportion of financials.

Another factor that may affect credit ratings is increased risk. This is proxied by the market model beta and residual risk. Finally, credit ratings may also be affected by a general decrease in the informativeness of accounting data. All of these factors will be examined in the next section.

IV. EMPIRICAL ANALYSIS

4.1 Original Model

The model for credit ratings follows the specification of Blume et al.   We are interested in predicting a discrete rating going from AAA to CC. The ordinal variable R_{it} is assigned a value of 8 if the firm-observation rating is AAA, 7 for AA, and so on until 1 for CC. The ordered probit specification then estimates boundary values μ_k that define bins for the unobserved continuous variable Z_{it}. For example, if Z_{it} falls above or is equal to μ_1, the observation is assigned a credit rating of 8, or AAA. If Z_{it} falls between μ_2 and μ_1, the observation is assigned a credit rating of 7, or AA, and so on. At the same time, the latent variable Z_{it} is related to the underlying observed accounting and financial variables through the regression:

$$Z_{it} = \alpha_t + \beta' X_{it} + \varepsilon_{it} \tag{1}$$

where α_t is a time-varying intercept, and β: is a vector of slope coefficients. Blume et al. found that the intercept displayed a significant downtrend, which they interpreted as evidence of tightening credit standards, *conditional* on "the explanatory variables used in the analysis."

Table 4 replicates the Blume et al. results on our data sample. The accounting variables include (i) four variables to represent interest coverage, using the same classification as in Blume et al. (1998),[17] (ii) operating margin, (iii) long-term debt leverage, and (iv) total debt leverage. We expect a higher credit rating for higher interest coverage, higher operating margin, and lower long-term and total debt leverage.[18]

The financial variables include the market value of the firm, market model beta and residual volatility. We expect a higher credit rating for larger firms, with a low beta and low residual risk. In the original specification, the last two variables are scaled by dividing by the cross-sectional mean for each year, which eliminates any trend in market and residual risk.

The left part of the table shows results for investment-grade issuers, which are consistent with Blume et al. The signs for the slope coefficients are identical to those found in the previous study and generally in line with what was expected. Most variables are significant.[19] The right panel reports results for our sample of speculative-grade issuers. The estimated annual intercepts are the most interesting aspect of the table. Figure 1 illustrates the trend in the intercept which is sharply negative for investment-grade sample, as in the Blume et al. paper. This negative trend

[17] Blume et al. (p. 1398) argue that the interest coverage ratio should enter the equation in a non-linear fashion. They first set C=0 for negative entries and C=100% for entries higher than 100%. The four variables are then set at c1=C for 0≤C<5% and c1=5 otherwise; c2=C-5 for 5%≤C<10%, c2=0 if C<5% and c2=5 if C≥10%; c3=C-10 for 10%≤C<20%, c3=0 if C<10% and c3=10 if C≥20%; c4=C-20 for 20%≤C and 0 otherwise.

[18] The latter two variables, however, are highly correlated, since total debt includes long-term debt. The collinearity problem may cause instability in the estimated slope coefficients.

[19] Blume et al. also report adjusted standard error, which correct for the correlations across years for the same firm. Intuitively, this is due to the fact that firms may have similar *X* observations and credit rating *R* across year. If so, the observations cannot be considered independent. The adjusted standard errors are typically three times the raw standard errors. Thus, we cannot infer significance without additional adjustments. The estimated coefficients, however, are unbiased. Thus, we can still focus on the trend in the intercept, which is the focus of our study.

gave rise to the interpretation of tightening credit standards. Holding other variables in this regression constant, this implies that the estimated credit rating of firms in this sample went down over time.

Figure 1, however, also displays the intercept for the speculative-grade sample. This shows no trend at all. Hence, the interpretation of tightening of credit standards should be restricted to investment-grade issuers. Any explanation of the trend in the intercept would also have to account for the sharply different behavior of these two rating categories.

Even for the investment-grade sample, the conclusion that rating standards have become more stringent over time could be due to the omission of risk variables that systematically change over time. Scaling the risk variables by the cross-sectional mean for each year eliminates the effect of changing risk over time. Over our sample period, the median residual risk of investment-grade issuers increased by 36%, and of speculative-grade issuers by 53%. Similarly, ignoring industry effects may also mask changing patterns in the aggregate credit risk profile.

4.2 Model with Industry and Risk Effects

We re-estimate Equation (1) adding industry dummies and without the cross-sectional adjustment in the market beta and idiosyncratic risk. Results are presented in Table 5. It is interesting to note that the utilities dummy is positive and very high, implying that the boundary values are higher for utilities than for industrials. In other words, holding the accounting and financial variables in this equation fixed, utilities are more highly rated than others. Given that the proportion of utilities has fallen in the investment-grade sample, this could potentially explain the decrease in intercept.

The intercepts are plotted in Figure 2. Accounting for changing industry and risk effects decreases the size of the time trend in the investment-grade intercept, but does not eliminate it. Thus these two variables alone do not fully account for the apparent tightening of credit standards for investment-grade firms.

4.3 Model with Industry, Risk, and Accounting Quality Effects

A third explanation is the decrease in informativeness of accounting information. This could be measured in several ways. In the context of the credit rating model, this can be measured by the R-square of the probit regression on the four accounting variables only. This procedure is similar to that of Brown, Lo, and Lys (1999), who document value relevance by the R-square of a regression of the stock price on earnings per share and book value per share. They document a decrease in this R-square, which is interpreted as a decrease in the value-relevance of accounting information, where relevance is measured in relation to the stock price. Here, we measure relevance in terms of the credit rating. As explained in the introduction, we assume that the manipulation of earnings data will bias the *reported* numbers to make the issuer look more creditworthy.

We re-estimate Equation (1) using the accounting explanatory variables only. Table 6 presents the annual R-squares for the investment-grade and speculative-grade categories. The numbers are plotted in Figure 3. It is interesting to note that the R-square is halved over this period for investment-grade issuers, from 21% to 11%, in a pattern of a progressive decline. Thus, accounting information is progressively becoming less useful to predict credit ratings for investment-grade firms. This pattern, however, is not observed for speculative-grade issuers, for which there is no discernible trend. Thus, our accounting quality variable seems highly correlated with the annual intercept.[20]

This decrease in the informativeness of accounting data could potentially explain the apparent tightening of credit standards. Rating agencies, faced with less informative accounting numbers, could rationally decrease the average rating over time.[21] Table 7 tests this hypothesis. The table reports the ordered probit regression with an additional variable taken as the R-square from the regression on accounting variables alone. The variable is significant for the investment-grade sample, but barely so for the speculative-grade sample. The positive sign implies that decreasing credit quality is associated with lower values of the R-squares, or accounting quality variables. Figure 4 plots the intercept from the ordered probit regression. By now, the trend in the investment-grade intercept has disappeared.

The measure used so far implicitly assumes that the declining accounting quality results from the opportunistic managerial manipulation of accounting data to make the firm appear less risky. S&P rationally puts less weight on *reported* accounting data to generate its credit ratings when the quality of accounting data decreases. To substantiate our argument, we proceed to estimate earnings management activities. Our measure is based on *discretionary accruals*.

Accounting earnings consist of cash flows and accounting adjustments called accruals (e.g., depreciation of equipment, provision for bad debt). Some of these accruals are non-discretionary because they result from normal business activities. In contrast, discretionary

[20] The Spearman rank correlation between the year dummies in Table 5 and the yearly R-squares in Table 6 is 0.829 (with a p-value of 0.00) for the investment grade sample and 0.212 (p-value of 0.40) for the speculative grade sample.

[21] Rating agencies have long maintained that accounting quality is an important determinant of ratings [S&P Corporate Ratings Criteria (2003)]. Recent academic research [e.g., Yu (2005)] confirms that lower disclosure quality of accounting information is associated with worse bond ratings and higher yield spread.

accruals are those that are primarily determined by managers, and have been shown to be a major means of earnings manipulation.

Following the earnings management literature (e.g., Dechow et al. (1995), Teoh, Welch and Wong (1998) and Hribar and Collins (2002)), we estimate discretionary accruals using a modified version of the Jones (1991) model. The modified Jones Model estimates non-discretionary accruals as a function of the change in revenues and the level of property, plant and equipment (PPE). Specifically, for each firm *i* in year *t*, we run a cross-sectional regression using other firms (two-digit SIC peers) *j≠i* in the same industry in year *t,*

$$\frac{\mathrm{TAC}_{jt}}{\mathrm{TA}_{jt-1}} = a_0\left(\frac{1}{\mathrm{TA}_{jt-1}}\right) + a_1\left(\frac{\Delta\mathrm{SALE}_{jt}}{\mathrm{TA}_{jt-1}}\right) + a_2\left(\frac{\mathrm{PPE}_{jt}}{\mathrm{TA}_{jt-1}}\right) + \varepsilon_{jt} \qquad (2)$$

where TAC_{jt} is total accruals, defined as income before extraordinary items (Compustat #123) minus cash flows from continuing operations (Compustat #308-Compustat #124),[22] $\Delta\mathrm{SALE}_{jt}$ is the change in sales revenues (Compustat #12), PPE_{jt} is gross property plant and equipment (Compsutat #7), and TA_{jt-1} is total assets (Compustat #6) in year *t-1*. We then use the estimated coefficients and the values of the variables for firm *i* in year *t* to measure nondiscretionary accruals (NDAC_{it}) as follows:

$$\mathrm{NDAC}_{it} = \hat{a}_0\left(\frac{1}{\mathrm{TA}_{it-1}}\right) + \hat{a}_1\left(\frac{\Delta\mathrm{SALE}_{it} - \Delta\mathrm{AR}_{it}}{\mathrm{TA}_{it-1}}\right) + \hat{a}_2\left(\frac{\mathrm{PPE}_{it}}{\mathrm{TA}_{it-1}}\right) \qquad (3)$$

where $\Delta\mathrm{AR}_{it}$ is the change in accounts receivable (Compustat #302).[23] Discretionary accruals

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[22]When operating cash flows data are not available (before 1987), total accruals are calculated as the change in current assets (Compustat #4) minus the change in current liabilities (Compustat #5) minus the change in cash and cash equivalents (Compustat #1) plus the change in current maturities of long-term debt (Compustat #34) minus depreciation and amortization expense (Compustat #14).

[23]The subtraction of accounts receivable from sales revenues constitutes the key modification to the original Jones Model. In contrast to the original model that ignores the firm's manipulation of earnings through revenue, the modified version assumes all changes in credit sales result from earnings management. Our results, however, are robust with respect to the alternative models.

(DAC_{it}) for firm *i* in year *t* are calculated as total accruals minus nondiscretionary accruals:

$$\mathrm{DAC}_{it} = \frac{\mathrm{TAC}_{it}}{\mathrm{TA}_{it-1}} - \mathrm{NDAC}_{it} \quad (4)$$

Table 8 reports cross-sectional medians of discretionary accruals by year for the sample period of 1985 to 2002. The numbers are plotted in Figure 5. The plot for the investment grade sample exhibits an upward trend, indicating an increase in earnings management activities over time. Most of the investment-grade entries are significant, moving from negative to positive values over this sample period.[24] In contrast, no discernible trend exists for the speculative grade firms.[25]

Table 9 summarizes the results of ordered probit analyses controlling for the changing earnings management activities. Recall that the four accounting variables in the rating models are averaged over three years. To be consistent, the estimates of discretionary accruals are also averaged over three years (t=0, -1 and -2). We measure earnings management for each sample year using the cross-sectional median of three-year moving averages of discretionary accruals for that year. The annual intercepts of the ordered probit regressions after controlling for the changing earnings management effect are depicted in Figure 6. As indicated in Table 9, the coefficient on the earnings management variable for the investment grade firms is significantly negative, consistent with the argument that increased (upward) earnings management is associated with lower credit ratings. In other words, when firms become more aggressive in implementing accounting rules, they tend to portray a much rosier picture than their true

[24] The correlation coefficients (Spearman and Pearson) between the yearly medians of discretionary accruals and the R-squares in Table 6 for the investment grade firms are equal to -0.62, significant at the one percent level. This is consistent with the argument that the declining value relevance of accounting data is likely caused by the increasing earnings management activities over time.

[25] It is interesting to note that S&P (2004b) uses a similar measure of earnings quality, based on the ratio between free cash flow and reported net income. The agency claims that "earnings quality over a reasonable period is a good measure of operating performance" (page 2).

underlying economics. As a rational response, rating agencies discount the reported accounting data and assign lower ratings to accurately reflect the firms' economic reality. Furthermore, the annual intercept does not exhibit a downward trend any more.[26] This provides no support for the hypothesis of tightening of credit standards, in line with our findings about default rates in Section II. For the speculative-grade firms, there is no discernible pattern in the intercepts.

Apparently, the increase in earnings management is most pronounced for investment-grade firms. As indicated in the Graham et al. (2004) survey, earnings management is more prevalent for firms that are large and have a high credit rating, which corresponds to our investment-grade sample. This can be ascribed to a number of factors. One is higher *pressure* on investment-grade firms to meet their earnings targets. Matsumoto (2002) reports that firms with higher institutional ownership, typically investment-grade firms, are more likely to manage earnings. This pressure is less severe for speculative-grade firms. Another factor is higher *capabilities* of investment-grade firms to manage their earnings. In its report on Engineering and Construction companies, for example, S&P (2004b) states that "the issue of earning quality occurs with traditional Tier 1 … companies", which are more likely to be rated investment grade. The agency explains that this is due to "the larger size, scope, and risks inherent in their project portfolios, and the increased likelihood of receiving advance payments." Thus, investment-grade firms can better manage earnings due to the scale of their operations, which makes it easier to shift income across operations and time. In addition, such firms are more likely to have access

[26] To assess the robustness of our results to the change in sample composition, we create a constant sample of 137 investment grade firms that have required data for the period of 1985 to 2002 (only three firms from the speculative grade sample survive the 18 years). Using the new subsample of investment grade firms, we first replicate the downward trend in the annual intercept and then document an increasing trend in earnings management over the sample period. After incorporating earnings management activities, there is no discernible pattern in the intercepts.

to exotic financing sources, such as the notorious Special Purpose Vehicles that were used by Enron to hide its debt.

Further, Gompers and Metrick (2001) document that institutional investors have increased their holdings of large companies' stocks over time. Growing institutional ownership could in turn create increasing pressure on these large firms, typically investment-grade firms, to meet and beat the market expectations as the penalty of failing to do so has grown more significant in recent years (Brown and Caylor 2004). Taken together, these factors might explain why earnings management is more prevalent for investment-grade firms than speculative-grade firms, why earnings management has become more pronounced over time for the investment-grade firms, and why rating agencies have adjusted their ratings for the former but not the latter.

V. CONCLUSIONS

Over the latest twenty years, the average credit rating of U.S. corporations has trended down. This is a troubling observation, because it could be interpreted as evidence that rating agencies have tightened their credit standards. If so, the same credit rating could mean different default probabilities at different point in time. This is a major issue for quantitative models of credit risk that rely on credit ratings.

This paper revisits the issue of tightening credit standards. We use the approach of Blume et al., who model the credit rating process as an ordered probit model based on accounting and financial data. They interpret the changing intercept as evidence of tightening credit standards. We confirm this finding for our sample of investment-grade issuers but find that this is not the case for speculative-grade issuers. At a minimum, tightening credit standards should be qualified by "for investment-grade issuers only."

We then explore alternative explanations of the changing intercept. As Blume et al. recognize, their results should be interpreted as evidence of tightening of credit standards only "in terms of the explanatory variables used in the analysis". To be consistent, any explanation has to apply to the investment-grade sample but not the speculative-grade sample. Explanations include a shift away from utilities, which are generally less risky than other industries, increasing volatility of market values, which increases the probability of default, and increased manipulation of accounting data that biases the accounting numbers toward making firms look more creditworthy. Indeed, we find that the value relevance of accounting data, for the credit ratings, has decreased over time for investment-grade but not speculative-grade issuers. We also find evidence of increased earnings management for investment-grade firms. After accounting for all of these effects, we find that the intercept remains stable for both samples, thus offering no support for the view that rating agencies have tightened their credit standards.

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Fig 1. Annual Intercept: Original Model

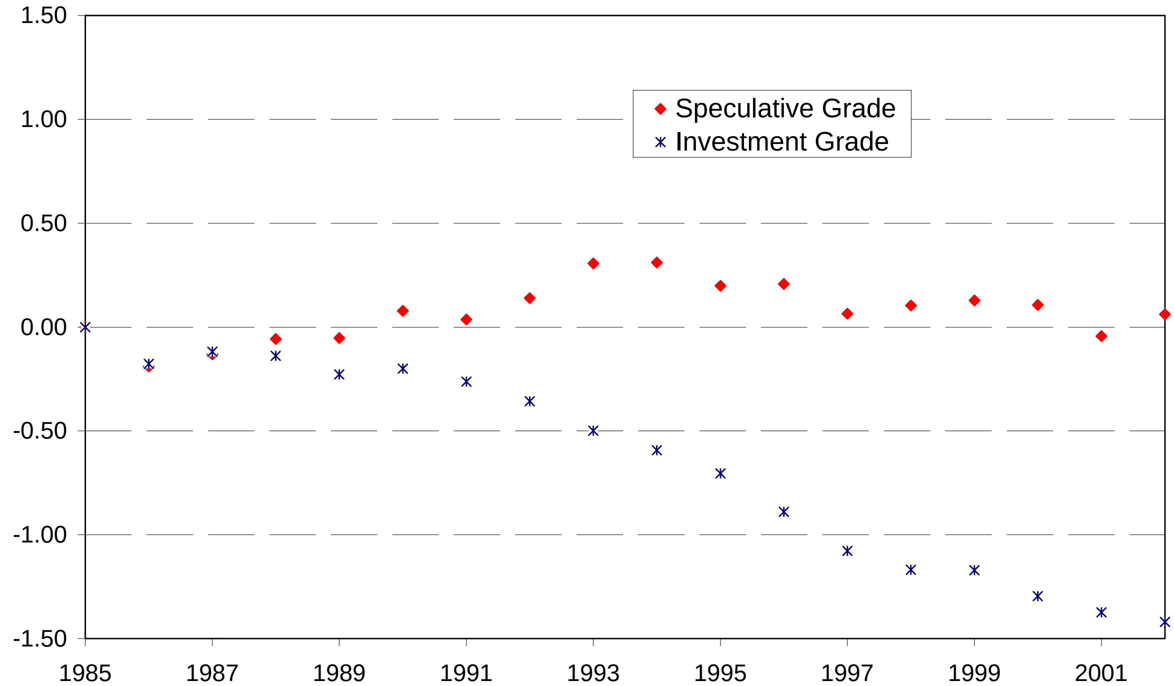

Fig 2. Annual Intercept: Model with Industry and Risk Effects

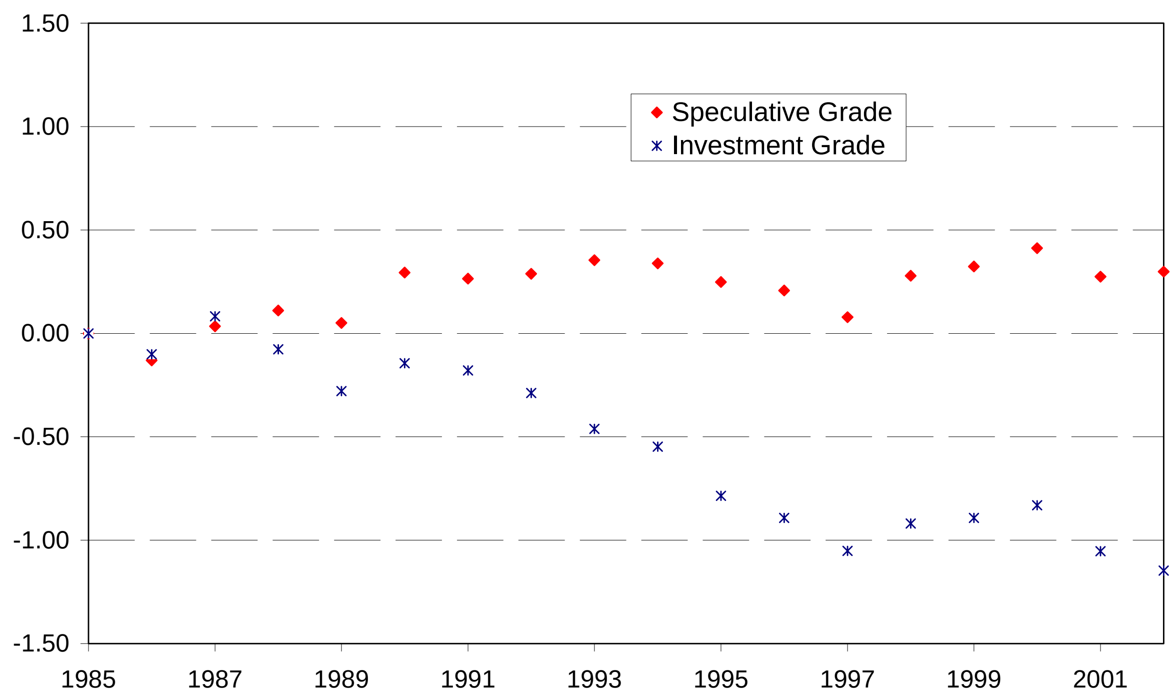

Fig 3. R-square from the Model with Accounting Data Only

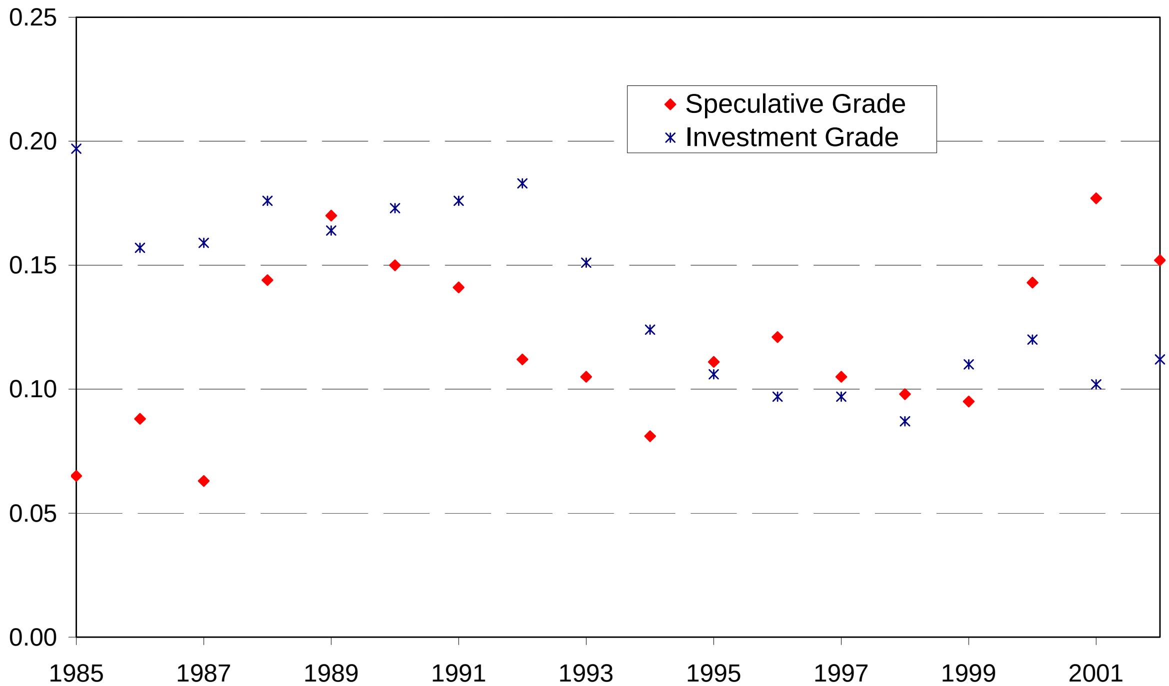

Fig 4. Annual Intercept: Model with Industry, Risk, and Accounting Quality Effects

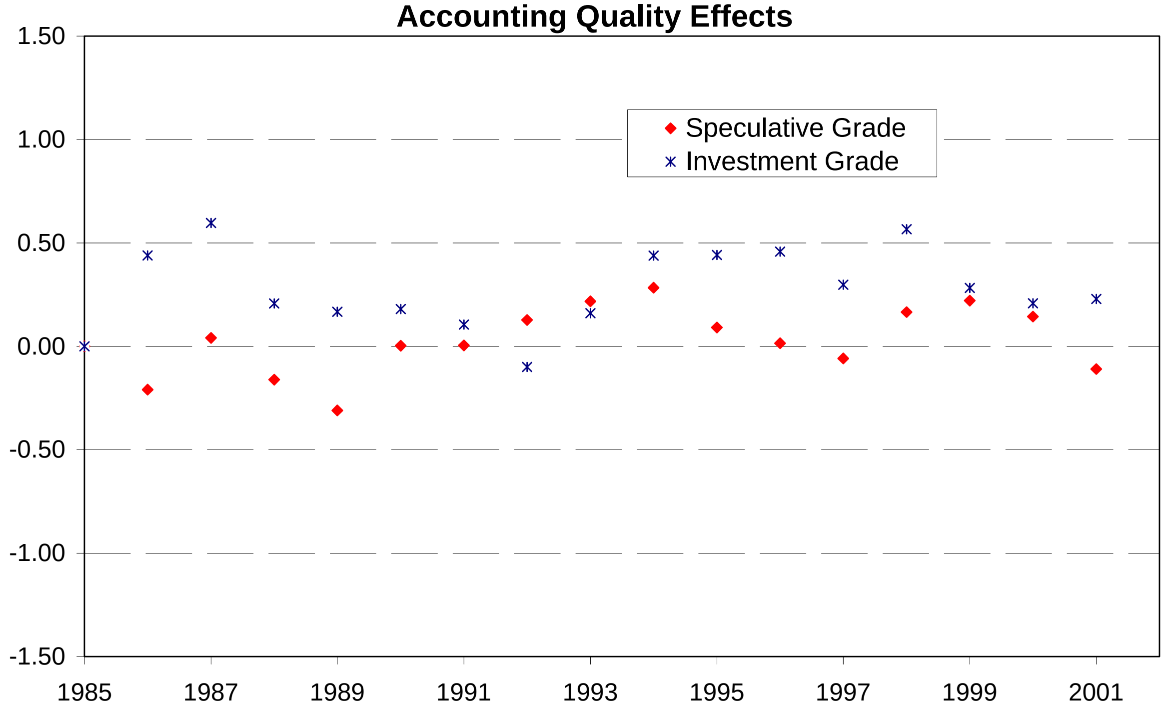

Fig 5. Earnings Management Effects Over Time

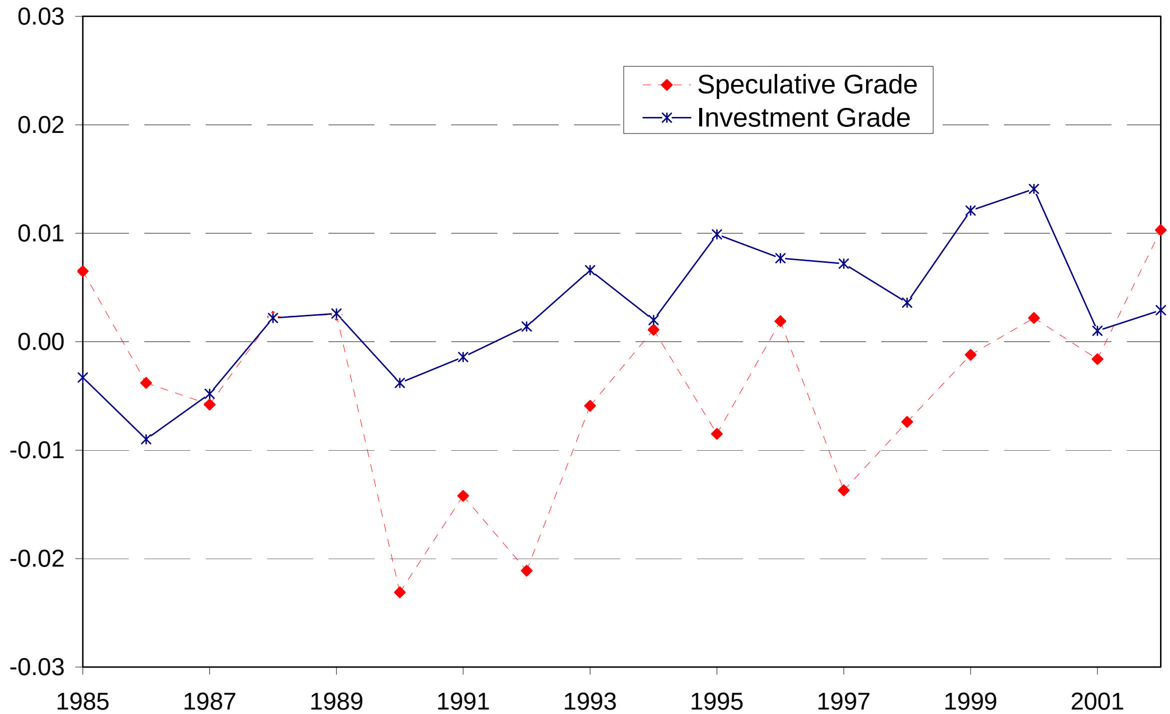

Fig 6. Annual Intercept: Model with Industry, Risk, and Earnings Management Effects

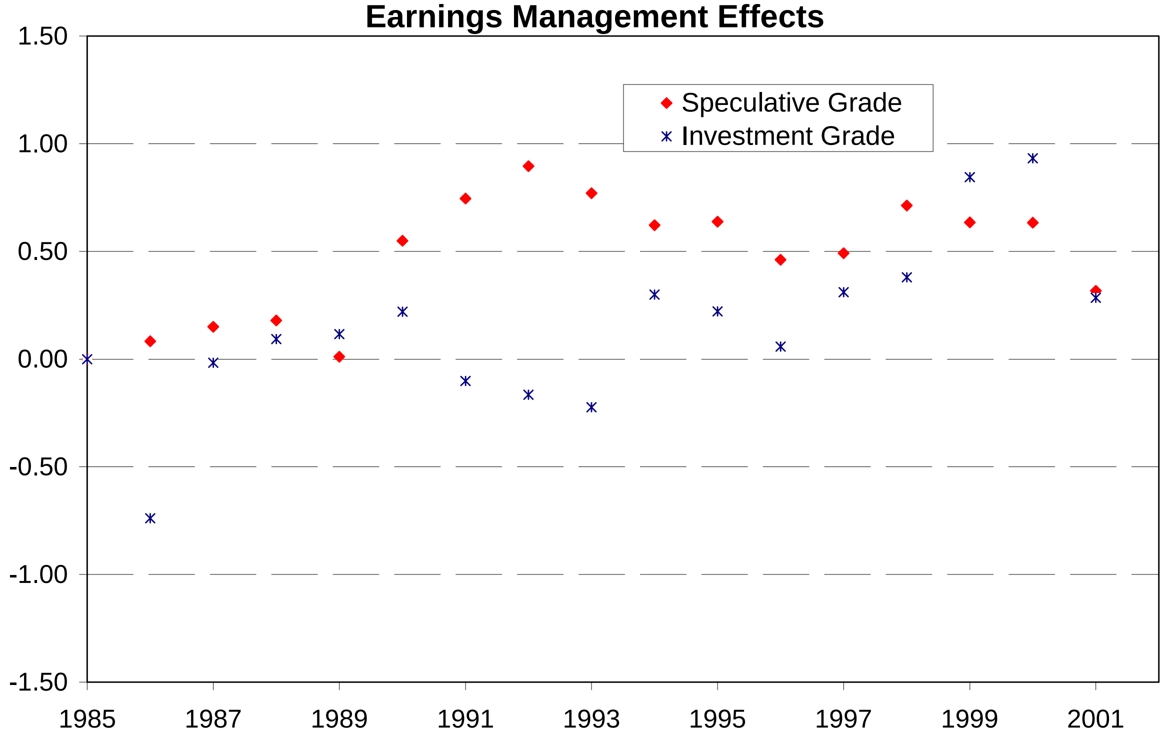

Table 1
S&P One-Year Historical Default Rates: 1981-2003
Percent (Standard Errors in Parentheses)

	Credit Rating														Class			
	Investment Grade								Speculative Grade									
	AAA		**AA**		**A**		**BBB**		**BB**		**B**		**CCC/C**		**Inv.Gr.**		**Spec.Gr.**	
1981	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	2.27	(1.59)	0.00	-	0.00	-	0.63	(0.44)
1982	0.00	-	0.00	-	0.21	(0.21)	0.34	(0.34)	4.19	(1.55)	3.14	(1.38)	23.08	(11.69)	0.19	(0.13)	4.42	(1.12)
1983	0.00	-	0.00	-	0.00	-	0.33	(0.33)	1.17	(0.82)	5.19	(1.79)	0.00	-	0.09	(0.09)	2.94	(0.92)
1984	0.00	-	0.00	-	0.00	-	0.67	(0.47)	1.16	(0.81)	3.39	(1.36)	15.79	(8.37)	0.17	(0.12)	2.98	(0.89)
1985	0.00	-	0.00	-	0.00	-	0.00	-	1.50	(0.86)	5.91	(1.66)	11.76	(7.81)	0.00	-	4.05	(0.96)
1986	0.00	-	0.00	-	0.18	(0.18)	0.33	(0.33)	1.33	(0.76)	8.30	(1.62)	18.75	(9.76)	0.15	(0.11)	5.66	(1.00)
1987	0.00	-	0.00	-	0.00	-	0.00	-	0.38	(0.38)	3.12	(0.93)	11.48	(4.08)	0.00	-	2.80	(0.63)
1988	0.00	-	0.00	-	0.00	-	0.00	-	1.05	(0.60)	3.88	(0.95)	21.43	(5.48)	0.00	-	4.12	(0.72)
1989	0.00	-	0.00	-	0.00	-	0.62	(0.44)	0.72	(0.51)	3.40	(0.89)	28.85	(6.28)	0.14	(0.10)	4.18	(0.74)
1990	0.00	-	0.00	-	0.00	-	0.59	(0.42)	3.57	(1.11)	8.52	(1.46)	31.82	(7.02)	0.14	(0.10)	7.99	(1.03)
1991	0.00	-	0.00	-	0.00	-	0.84	(0.48)	2.53	(1.02)	13.73	(2.04)	32.76	(6.16)	0.20	(0.12)	11.05	(1.30)
1992	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	7.66	(1.78)	27.08	(6.41)	0.00	-	5.88	(1.04)
1993	0.00	-	0.00	-	0.00	-	0.00	-	0.35	(0.35)	2.64	(1.06)	14.63	(5.52)	0.00	-	2.36	(0.65)
1994	0.00	-	0.00	-	0.13	(0.13)	0.00	-	0.28	(0.28)	3.10	(0.96)	18.18	(8.22)	0.05	(0.05)	2.12	(0.54)
1995	0.00	-	0.00	-	0.00	-	0.17	(0.17)	0.97	(0.48)	4.34	(1.03)	28.00	(8.98)	0.04	(0.04)	3.38	(0.63)
1996	0.00	-	0.00	-	0.00	-	0.00	-	0.66	(0.38)	2.86	(0.81)	4.00	(3.92)	0.00	-	1.77	(0.44)
1997	0.00	-	0.00	-	0.00	-	0.38	(0.22)	0.19	(0.19)	3.41	(0.84)	12.00	(6.50)	0.11	(0.06)	1.95	(0.43)
1998	0.00	-	0.00	-	0.00	-	0.52	(0.23)	0.94	(0.38)	4.54	(0.80)	41.38	(9.15)	0.17	(0.08)	3.62	(0.51)
1999	0.00	-	0.17	(0.17)	0.09	(0.09)	0.19	(0.14)	1.17	(0.39)	7.04	(0.86)	34.78	(5.73)	0.13	(0.07)	5.52	(0.55)
2000	0.00	-	0.00	-	0.09	(0.09)	0.36	(0.18)	1.16	(0.36)	7.61	(0.87)	33.73	(5.19)	0.16	(0.07)	5.80	(0.54)
2001	0.00	-	0.00	-	0.25	(0.14)	0.41	(0.18)	2.92	(0.56)	10.87	(1.03)	45.95	(4.73)	0.25	(0.09)	9.21	(0.66)
2002	0.00	-	0.00	-	0.08	(0.08)	1.20	(0.30)	3.10	(0.59)	8.53	(0.97)	46.24	(3.79)	0.52	(0.13)	9.49	(0.68)
2003	0.00	-	0.00	-	0.00	-	0.21	(0.12)	0.71	(0.27)	3.60	(0.64)	34.13	(3.67)	0.09	(0.05)	4.71	(0.47)
Average:																		
1981-2003	0.00	-	0.01	(0.01)	0.04	(0.02)	0.31	(0.05)	1.31	(0.11)	5.52	(0.23)	23.30	(1.23)	0.11	(0.02)	4.64	(0.14)
Firm-years		3,511		10,138		17,890		13,870		9,817		10,046		1,180		45,409		21,043
Subsamples:																		
1985-1993	0.00	-	0.00	-	0.02	(0.02)	0.26	(0.09)	1.27	(0.23)	6.35	(0.46)	22.06	(2.09)	0.07	(0.02)	5.34	(0.30)
1994-2002	0.00	-	0.02	(0.02)	0.07	(0.03)	0.36	(0.07)	1.27	(0.15)	5.81	(0.31)	29.36	(1.92)	0.16	(0.03)	4.76	(0.19)
Equality t-test		-		-		1.5		0.8		0.0		-1.0		2.6		2.6		-1.6
Slope t-test						0.6		1.0		-0.1		1.2		4.1		1.8		1.7

Notes: The table reports default rates for global firms within a rating class over the next year, as compiled by Standard and Poor's (2004).
Defaults are described by credit rating class, from AAA down to CCC/C; ratings at or above BBB are investment grade, below BBB speculative grade.
Default rates are measured in percent and accompanied by their standard error from the binomial distribution.
The bottom part of the table reports the average default rate over the total period 1981-2003 and subperiods 1985-1993 and 1994-2002,
as well as asymptotic t-tests of equal default rates across subperiods.
The slope t-test is for a regression of the annual default rate on a time trend and tests whether the slope is significantly different from zero.

Table 2
Distribution of Sample Firms by S&P Credit Rating and Year

Panel A: Number

	Credit Rating								Grade		
Year	AAA	AA	A	BBB	BB	B	CCC	CC	Investment	Speculative	Total
1985	13	87	163	103	60	66	4	0	366	130	496
1986	17	93	198	149	122	148	19	0	457	289	746
1987	17	93	200	145	140	170	22	0	455	332	787
1988	18	87	208	139	130	148	14	0	452	292	744
1989	18	85	200	152	124	122	15	0	455	261	716
1990	16	85	188	159	116	91	14	1	448	222	670
1991	15	84	196	160	108	84	13	3	455	208	663
1992	18	80	198	188	128	91	13	4	484	236	720
1993	15	77	215	200	159	100	5	1	507	265	772
1994	16	79	219	225	182	110	8	0	539	300	839
1995	18	75	242	242	183	127	7	0	577	317	894
1996	20	71	262	279	215	146	5	1	632	367	999
1997	19	68	268	327	237	192	7	1	682	437	1,119
1998	12	75	273	352	282	193	13	5	712	493	1,205
1999	13	68	267	369	288	193	12	1	717	494	1,211
2000	12	57	250	365	285	195	16	1	684	497	1,181
2001	11	50	246	375	290	186	20	3	682	499	1,181
2002	10	34	229	350	313	185	22	5	623	525	1,148
Total	278	1348	4022	4279	3362	2547	229	26	9,927	6,164	16,091

Panel B: Percentage

year	AAA	AA	A	BBB	BB	B	CCC	CC	Invest.	Spec.	Total
1985	2.6	17.5	32.9	20.8	12.1	13.3	0.8	0.0	73.8	26.2	100
1986	2.3	12.5	26.5	20.0	16.4	19.8	2.5	0.0	61.3	38.7	100
1987	2.2	11.8	25.4	18.4	17.8	21.6	2.8	0.0	57.8	42.2	100
1988	2.4	11.7	28.0	18.7	17.5	19.9	1.9	0.0	60.8	39.2	100
1989	2.5	11.9	27.9	21.2	17.3	17.0	2.1	0.0	63.5	36.5	100
1990	2.4	12.7	28.1	23.7	17.3	13.6	2.1	0.1	66.9	33.1	100
1991	2.3	12.7	29.6	24.1	16.3	12.7	2.0	0.5	68.6	31.4	100
1992	2.5	11.1	27.5	26.1	17.8	12.6	1.8	0.6	67.2	32.8	100
1993	1.9	10.0	27.8	25.9	20.6	13.0	0.6	0.1	65.7	34.3	100
1994	1.9	9.4	26.1	26.8	21.7	13.1	1.0	0.0	64.2	35.8	100
1995	2.0	8.4	27.1	27.1	20.5	14.2	0.8	0.0	64.5	35.5	100
1996	2.0	7.1	26.2	27.9	21.5	14.6	0.5	0.1	63.3	36.7	100
1997	1.7	6.1	23.9	29.2	21.2	17.2	0.6	0.1	60.9	39.1	100
1998	1.0	6.2	22.7	29.2	23.4	16.0	1.1	0.4	59.1	40.9	100
1999	1.1	5.6	22.0	30.5	23.8	15.9	1.0	0.1	59.2	40.8	100
2000	1.0	4.8	21.2	30.9	24.1	16.5	1.4	0.1	57.9	42.1	100
2001	0.9	4.2	20.8	31.8	24.6	15.7	1.7	0.3	57.7	42.3	100
2002	0.9	3.0	19.9	30.5	27.3	16.1	1.9	0.4	54.3	45.7	100
Total	1.7	8.4	25.0	26.6	20.9	15.8	1.4	0.2	61.7	38.3	100

The sample consists of a panel of 16,091 issuer credit ratings covered by S&P from 1985 to 2002. Credit ratings data are from the 2002 annual Compustat. Panel A presents the number of issuer ratings by year, and Panel B presents the percentage distribution by year.

Table 3
Distribution of Firms with S&P Credit Rating by Industry Group and Year

Panel A: Investment-Grade Firms

Year	Transportations (%)	Utilities(%)	Financials(%)	Industrials(%)	Total (%)	Total (#)
1985	4.4	20.8	6.6	68.3	100	366
1986	4.6	20.4	7.0	68.1	100	457
1987	4.2	20.7	6.6	68.6	100	455
1988	3.8	20.8	7.3	68.1	100	452
1989	4.0	19.3	7.5	69.2	100	455
1990	3.6	20.8	5.1	70.5	100	448
1991	4.2	20.7	4.2	71.0	100	455
1992	3.3	19.8	4.5	72.3	100	484
1993	3.4	18.1	6.9	71.6	100	507
1994	3.3	17.8	11.5	67.3	100	539
1995	2.9	17.2	11.6	68.3	100	577
1996	3.5	16.0	12.2	68.4	100	632
1997	2.9	15.4	11.7	69.9	100	682
1998	3.4	15.4	13.3	67.8	100	712
1999	3.5	15.6	13.5	67.4	100	717
2000	3.8	15.2	13.3	67.7	100	684
2001	3.5	15.1	13.5	67.9	100	682
2002	4.2	14.4	14.9	66.5	100	623
Total						9,927

Panel B: Speculative-Grade Firms

Year	Transportations(%)	Utilities(%)	Financials(%)	Industrials(%)	Total (%)	Total (#)
1985	5.4	4.6	3.8	86.2	100	130
1986	2.8	2.4	4.8	90.0	100	289
1987	3.0	2.7	4.8	89.5	100	332
1988	4.5	2.7	5.1	87.7	100	292
1989	3.8	5.0	4.6	86.6	100	261
1990	3.2	3.6	5.4	87.8	100	222
1991	2.4	4.8	7.7	85.1	100	208
1992	3.4	5.9	4.7	86.0	100	236
1993	4.2	6.0	4.9	84.9	100	265
1994	4.3	5.7	4.0	86.0	100	300
1995	4.1	5.4	4.7	85.8	100	317
1996	3.5	4.4	3.3	88.8	100	367
1997	5.3	3.2	3.9	87.6	100	437
1998	5.1	2.0	4.3	88.6	100	493
1999	3.8	1.8	5.1	89.3	100	494
2000	4.0	2.2	5.0	88.7	100	497
2001	4.6	2.6	4.8	88.0	100	499
2002	4.2	3.8	5.5	86.5	100	525
Total						6,164

The overall sample consists of a panel of 16,091 issuer credit ratings (9,927 investment grade ratings and 6,164 speculative grade ratings) covered by S&P from 1985 to 2002. Credit ratings data are from the 2002 annual Compustat. Panel A and B give the percentage breakdown of credit ratings and the total by industry group and year for the investment-grade and speculative-grade firms, respectively.

Table 4
Ordered Probit Model Estimates for Investment- and Speculative-Grade Firms

	Investment Grade			Speculative Grade		
	Coefficient	Standard Error	P-Value	Coefficient	Standard Error	P-Value
Interest Coverage c1	0.311	0.018	0.00	0.250	0.016	0.00
Interest Coverage c2	0.020	0.010	0.04	-0.119	0.022	0.00
Interest Coverage c3	0.042	0.006	0.00	-0.004	0.016	0.79
Interest Coverage c4	-0.008	0.002	0.00	-0.001	0.003	0.86
Operating Margin	1.801	0.106	0.00	0.018	0.119	0.88
LT Debt Leverage	-4.090	0.172	0.00	0.054	0.175	0.76
Total Debt Leverage	1.128	0.138	0.00	-0.497	0.166	0.00
Market Value	0.405	0.011	0.00	0.285	0.015	0.00
Adj. Market Model Beta	-0.309	0.024	0.00	-0.124	0.026	0.00
Adj. Idiosyncratic Risk	-1.165	0.049	0.00	-0.880	0.051	0.00
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	-0.177	0.081	0.03	-0.190	0.131	0.15
1987	-0.118	0.081	0.15	-0.131	0.128	0.31
1988	-0.138	0.082	0.09	-0.057	0.131	0.66
1989	-0.228	0.082	0.01	-0.053	0.134	0.69
1990	-0.200	0.082	0.02	0.078	0.138	0.57
1991	-0.263	0.082	0.00	0.036	0.140	0.79
1992	-0.358	0.082	0.00	0.139	0.137	0.31
1993	-0.499	0.081	0.00	0.306	0.136	0.02
1994	-0.593	0.080	0.00	0.311	0.133	0.02
1995	-0.705	0.080	0.00	0.198	0.132	0.13
1996	-0.890	0.078	0.00	0.207	0.130	0.11
1997	-1.078	0.078	0.00	0.064	0.126	0.61
1998	-1.169	0.078	0.00	0.104	0.125	0.40
1999	-1.171	0.078	0.00	0.128	0.125	0.30
2000	-1.296	0.080	0.00	0.106	0.125	0.39
2001	-1.373	0.080	0.00	-0.044	0.125	0.73
2002	-1.420	0.081	0.00	0.062	0.124	0.62

The estimates of ordered probit regressions are based on a panel of 9927 investment-grade ratings and 6164 speculative-grade ratings covered by S&P from 1985 to 2002, respectively. All required data are obtained from Compustat and CRSP daily stock files. The dependent variable is S&P long-term issuer credit rating. Each of the eight categorical ratings is assigned with an integer on an eight point scale (8 for AAA, 1 for CC). Interest coverage is the ratio of operating income after depreciation plus interest expense to interest expense, and it is treated in a non-linear fashion, as defined in footnote 11. Operating margin is the ratio of operating income before depreciation to net sales. LT debt leverage is the ratio of long-term debt to total assets. Total debt leverage is the ratio of total debt to total assets. Three-year averages of these ratios are used in regressions. Market value is the natural logarithm of the yearend market value of equity deflated by the CPI. Adj. market model beta is estimated from the market model using daily stock returns in each calendar year. The beta estimates are controlled for nonsynchronous trading effects using the Dimson (1979) procedure. Adj. idiosyncratic risk is the standard error from the market model. The estimates of betas and idiosyncratic risks for each year are further adjusted for the variation in the means of betas and idiosyncratic risks over time, respectively (divided by their respective cross-sectional mean of that year). P-values are two-sided.

Table 5
Ordered Probit Model Estimates for Investment-Grade and Speculative-Grade Firms, Controlling for Industry Effect and Changes in Equity Risk Measures

	Investment Grade			Speculative Grade		
	Coefficient	Standard Error	P-Value	Coefficient	Standard Error	P-Value
Interest Coverage c1	0.347	0.019	0.00	0.269	0.016	0.00
Interest Coverage c2	0.050	0.010	0.00	-0.132	0.022	0.00
Interest Coverage c3	0.034	0.007	0.00	-0.003	0.016	0.86
Interest Coverage c4	-0.008	0.002	0.00	-0.001	0.003	0.87
Operating Margin	1.304	0.116	0.00	-0.016	0.120	0.89
LT Debt Leverage	-4.733	0.191	0.00	0.061	0.176	0.73
Total Debt Leverage	1.412	0.143	0.00	-0.553	0.166	0.00
Market Value	0.471	0.011	0.00	0.319	0.016	0.00
Market Model Beta	-0.306	0.033	0.00	-0.152	0.027	0.00
Idiosyncratic Risk	-51.506	2.870	0.00	-16.145	1.324	0.00
Utilities Dummy	0.972	0.085	0.00	0.301	0.131	0.02
Financials Dummy	0.252	0.088	0.00	-0.482	0.112	0.00
Industrials Dummy	0.138	0.078	0.08	-0.238	0.084	0.00
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	-0.101	0.082	0.21	-0.131	0.130	0.32
1987	0.083	0.083	0.31	0.034	0.128	0.79
1988	-0.077	0.082	0.35	0.110	0.131	0.40
1989	-0.278	0.082	0.00	0.051	0.134	0.70
1990	-0.144	0.083	0.08	0.294	0.138	0.03
1991	-0.179	0.083	0.03	0.265	0.140	0.06
1992	-0.288	0.082	0.00	0.288	0.137	0.04
1993	-0.461	0.082	0.00	0.354	0.135	0.01
1994	-0.547	0.080	0.00	0.338	0.133	0.01
1995	-0.786	0.080	0.00	0.249	0.132	0.06
1996	-0.892	0.080	0.00	0.208	0.130	0.11
1997	-1.052	0.080	0.00	0.078	0.127	0.54
1998	-0.919	0.081	0.00	0.279	0.125	0.03
1999	-0.892	0.086	0.00	0.324	0.128	0.01
2000	-0.831	0.092	0.00	0.412	0.128	0.00
2001	-1.054	0.086	0.00	0.274	0.127	0.03
2002	-1.147	0.084	0.00	0.299	0.126	0.02

The estimates of ordered probit regressions are based on a panel of 9927 investment-grade ratings and 6164 speculative-grade ratings covered by S&P from 1985 to 2002, respectively. All required data are obtained from Compustat and CRSP daily stock files. The dependent variable is S&P long-term issuer credit rating. Each of the eight categorical ratings is assigned with an integer on an eight point scale (8 for AAA, 1 for CC). Interest coverage is the ratio of operating income after depreciation plus interest expense to interest expense, and it is treated in a non-linear fashion, as defined in footnote 11. Operating margin is the ratio of operating income before depreciation to net sales. LT debt leverage is the ratio of long-term debt to total assets. Total debt leverage is the ratio of total debt to total assets. Three-year averages of these ratios are used in regressions. Market value is the natural logarithm of the yearend market value of equity deflated by the CPI. Market model beta is estimated from the market model using daily stock returns in each calendar year. The beta estimates are controlled for nonsynchronous trading effects using the Dimson (1979) procedure. Idiosyncratic risk is the standard error from the market model. Each of the three industry dummies (utilities, financials, industrials) takes value of one if the firm belongs to the corresponding industry group and zero otherwise (transportations dummy is suppressed to avoid dummy trap). P-values are two-sided.

Table 6
Pseudo-R^2 from Ordered Probit Regression of Credit Ratings on Accounting Ratios by Year for the Investment-Grade and Speculative-Grade Firms

Year	Investment Grade	Speculative Grade
1985	0.213	0.060
1986	0.164	0.092
1987	0.154	0.064
1988	0.170	0.145
1989	0.156	0.162
1990	0.171	0.147
1991	0.175	0.139
1992	0.180	0.090
1993	0.154	0.110
1994	0.126	0.095
1995	0.110	0.108
1996	0.104	0.118
1997	0.105	0.100
1998	0.091	0.084
1999	0.110	0.087
2000	0.118	0.132
2001	0.109	0.177
2002	0.105	0.145

Yearly McFadden pseudo-R^2 estimates are obtained from ordered probit regression of credit rating on four accounting ratios by year for the investment- and speculative-grade firms, respectively. There are 9927 investment grade ratings and 6164 speculative grade ratings covered by S&P from 1985 to 2002. The accounting ratios include interest coverage (the ratio of operating income after depreciation plus interest expense to interest expense), operating margin (the ratio of operating income before depreciation to net sales), LT debt leverage (the ratio of long-term debt to total assets) and total debt leverage (the ratio of total debt to total assets). Three-year averages of these ratios are used in regression analysis.

Table 7
Ordered Probit Model Estimates for Investment-Grade and Speculative-Grade Firms, Controlling for Industry Effect and Changes in Equity Risk Measures and Accounting Quality

	Investment Grade			Speculative Grade		
	Coefficient	Standard Error	P-Value	Coefficient	Standard Error	P-Value
Interest Coverage c1	0.347	0.019	0.00	0.269	0.016	0.00
Interest Coverage c2	0.050	0.010	0.00	-0.132	0.022	0.00
Interest Coverage c3	0.034	0.006	0.00	-0.003	0.016	0.86
Interest Coverage c4	-0.008	0.002	0.00	-0.001	0.003	0.87
Operating Margin	1.304	0.116	0.00	-0.016	0.120	0.89
LT Debt Leverage	-4.733	0.191	0.00	0.061	0.176	0.73
Total Debt Leverage	1.412	0.143	0.00	-0.553	0.166	0.00
Market Value	0.471	0.011	0.00	0.319	0.016	0.00
Market Model Beta	-0.306	0.033	0.00	-0.152	0.027	0.00
Idiosyncratic Risk	-51.506	2.871	0.00	-16.145	1.324	0.00
Utilities Dummy	0.972	0.085	0.00	0.301	0.131	0.02
Financials Dummy	0.252	0.088	0.00	-0.482	0.112	0.00
Industrials Dummy	0.138	0.078	0.08	-0.238	0.084	0.00
Accounting Quality	13.498	0.991	0.00	3.435	1.446	0.02
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	0.439	0.069	0.00	-0.210	0.109	0.05
1987	0.597	0.069	0.00	0.041	0.130	0.75
1988	0.207	0.073	0.00	-0.161	0.092	0.08
1989	0.167	0.071	0.02	-0.310	0.111	0.00
1990	0.180	0.073	0.01	0.003	0.104	0.98
1991	0.105	0.074	0.16	0.004	0.102	0.97
1992	-0.100	0.075	0.19	0.127	0.101	0.21
1993	0.160	0.067	0.02	0.217	0.103	0.04
1994	0.438	0.071	0.00	0.283	0.117	0.02
1995	0.442	0.078	0.00	0.091	0.095	0.34
1996	0.458	0.082	0.00	0.015	0.088	0.86
1997	0.298	0.080	0.00	-0.059	0.090	0.51
1998	0.566	0.086	0.00	0.165	0.093	0.07
1999	0.282	0.074	0.00	0.221	0.097	0.02
2000	0.208	0.075	0.01	0.144	0.080	0.07
2001	0.229	0.078	0.00	-0.110	0.100	0.27

The estimates of ordered probit regressions are based on a panel of 9927 investment-grade ratings and 6164 speculative-grade ratings covered by S&P from 1985 to 2002, respectively. The dependent variable is S&P long-term issuer credit rating. Interest coverage is the ratio of operating income after depreciation plus interest expense to interest expense, and it is treated in a non-linear fashion, as defined in footnote 11. Operating margin is the ratio of operating income before depreciation to net sales. LT debt leverage is the ratio of long-term debt to total assets. Total debt leverage is the ratio of total debt to total assets. Three-year averages of these ratios are used in regressions. Market value is the natural logarithm of the yearend market value of equity deflated by the CPI. Market model beta is estimated from the market model using daily stock returns in each calendar year. The beta estimates are controlled for nonsynchronous trading effects using the Dimson (1979) procedure. Idiosyncratic risk is the standard error from the market model. Each of the three industry dummies (utilities, financials, industrials) takes value of one if the firm belongs to the corresponding industry group and zero otherwise (transportation dummy is suppressed to avoid dummy trap). Accounting quality is the yearly McFadden pseudo-R2 estimates obtained from ordered probit regression of credit rating on the four accounting ratios by year for the investment and speculative grade firms, respectively (see Table 6). P-values are two-sided.

Table 8
Earnings Management Activities by Year for Investment-Grade and Speculative-Grade Firms

Year	Investment-Grade		Speculative-Grade	
	Obs.	Disc. Accruals	Obs.	Disc. Accruals
1985	347	-0.0033*	123	0.0065
1986	436	-0.0090*	257	-0.0038
1987	413	-0.0048*	294	-0.0058
1988	381	0.0022	259	0.0023
1989	381	0.0026	237	0.0025
1990	389	-0.0038*	200	-0.0231*
1991	407	-0.0014*	192	-0.0142*
1992	431	0.0014	219	-0.0211*
1993	440	0.0066*	246	-0.0059
1994	460	0.0020	286	0.0011
1995	490	0.0099*	303	-0.0085
1996	536	0.0077*	349	0.0019
1997	574	0.0072*	417	-0.0137*
1998	595	0.0036	465	-0.0074
1999	592	0.0121*	469	-0.0012
2000	567	0.0141*	475	0.0022
2001	572	0.0010	479	-0.0016
2002	527	0.0029*	504	0.0103*
Total (#)	8538		5774	

Earnings management activities in a given year are measured by the median of discretionary accruals of all sample firms in that year. Discretionary accruals are estimated using the Modified Jones Model. Specifically, for each firm *i* in year *t*, we run a cross-sectional regression using other firms (two-digit SIC peers) $j \neq i$ in the same industry in year *t*,

$$\frac{TAC_{jt}}{TA_{jt-1}} = a_0\left(\frac{1}{TA_{jt-1}}\right) + a_1\left(\frac{\Delta SALE_{jt}}{TA_{jt-1}}\right) + a_2\left(\frac{PPE_{jt}}{TA_{jt-1}}\right) + \varepsilon_{jt}$$

where TAC_{jt} is total accruals, defined as income before extraordinary items minus cash flows from continuing operations, $\Delta SALE_{jt}$ is the change in sales revenues, PPE_{jt} is gross property plant and equipment, and TA_{jt-1} is total assets in year *t-1*. We then use the estimated coefficients and the values of the variables for firm *i* in year *t* to measure nondiscretionary accruals ($NDAC_{it}$) as follows:

$$NDAC_{it} = \hat{a}_0\left(\frac{1}{TA_{it-1}}\right) + \hat{a}_1\left(\frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}}\right) + \hat{a}_2\left(\frac{PPE_{it}}{TA_{it-1}}\right)$$

where ΔAR_{it} is the change in accounts receivable. Discretionary accruals (DAC_{it}) for firm *i* in year *t* are calculated as total accruals minus nondiscretionary accruals. * indicates the 5% significance (two-sided) of Wilcoxon signed-rank test of the median being different from zero.

Table 9
Ordered Profit Model Estimates for Investment-Grade and Speculative-Grade Firms, Controlling for Industry Effect and Changes in Equity Risk Measures and Earnings Management

	Investment-Grade			Speculative-Grade		
	Coefficient	Standard Error	P-Value	Coefficient	Standard Error	P-Value
Interest Coverage c1	0.382	0.021	0.00	0.271	0.017	0.00
Interest Coverage c2	0.052	0.011	0.00	-0.135	0.022	0.00
Interest Coverage c3	0.039	0.007	0.00	-0.001	0.016	0.96
Interest Coverage c4	-0.010	0.002	0.00	-0.000	0.003	0.94
Operating Margin	1.055	0.136	0.00	-0.099	0.128	0.44
LT Debt Leverage	-4.842	0.214	0.00	0.179	0.189	0.35
Total Debt Leverage	1.654	0.168	0.00	-0.657	0.181	0.00
Market Value	0.461	0.012	0.00	0.323	0.016	0.00
Market Model Beta	-0.329	0.036	0.00	-0.168	0.028	0.00
Idiosyncratic Risk	-51.601	3.111	0.00	-15.878	1.383	0.00
Utilities Dummy	1.022	0.089	0.00	0.203	0.133	0.13
Financials Dummy	0.127	0.101	0.21	-0.698	0.123	0.00
Industrials Dummy	0.171	0.081	0.04	-0.337	0.088	0.00
Earnings Management	-115.1	9.331	0.00	22.993	9.867	0.02
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	-0.739	0.122	0.00	0.083	0.220	0.71
1987	-0.017	0.093	0.85	0.150	0.186	0.42
1988	0.093	0.083	0.26	0.179	0.166	0.28
1989	0.116	0.078	0.13	0.011	0.132	0.93
1990	0.220	0.777	0.00	0.549	0.252	0.03
1991	-0.102	0.086	0.23	0.746	0.326	0.02
1992	-0.166	0.083	0.04	0.896	0.371	0.02
1993	-0.223	0.078	0.00	0.771	0.293	0.01
1994	0.300	0.074	0.00	0.622	0.233	0.01
1995	0.222	0.077	0.00	0.638	0.272	0.02
1996	0.058	0.073	0.43	0.461	0.223	0.04
1997	0.311	0.090	0.00	0.492	0.292	0.09
1998	0.380	0.086	0.00	0.713	0.303	0.02
1999	0.845	0.112	0.00	0.635	0.255	0.01
2000	0.933	0.115	0.00	0.633	0.211	0.00
2001	0.285	0.089	0.00	0.317	0.146	0.03

The estimates of ordered probit regressions are based on a panel of 8538 investment-grade ratings and 5774 speculative-grade ratings covered by S&P from 1985 to 2002, respectively. The dependent variable is S&P long-term issuer credit rating. Interest coverage is the ratio of operating income after depreciation plus interest expense to interest expense, and it is treated in a non-linear fashion, as defined in footnote 11. Operating margin is the ratio of operating income before depreciation to net sales. LT debt leverage is the ratio of long-term debt to total assets. Total debt leverage is the ratio of total debt to total assets. Three-year averages of these ratios are used in regressions. Market value is the natural logarithm of the yearend market value of equity deflated by the CPI. Market model beta is estimated from the market model using daily stock returns in each calendar year. The beta estimates are controlled for nonsynchronous trading effects using the Dimson (1979) procedure. Idiosyncratic risk is the standard error from the market model. Each of the three industry dummies (utilities, financials, industrials) takes value of one if the firm belongs to the corresponding industry group and zero otherwise (transportation dummy is suppressed to avoid dummy trap). Earnings management is the yearly median of three-year moving averages of discretionary accruals estimated from the Modified Jones Model (see Table 8 for details). P-values are two-sided.