Tightening Credit Standards: The Role of Accounting Quality

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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, Lim, and MacKinlay (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 reexamine the causes of the observed decreases in average credit ratings in several ways. First, we show that this downward trend does not apply to speculative-grade issuers. Second, our analysis of structural shifts in investment-grade issuers reveals that the apparent tightening of standards reported by Blume et al. (1998) can be attributed primarily to changes in accounting quality over time. Specifically, we find that the value-relevance of commonly used accounting ratios to creditors decreased and that earnings management increased for investment-grade firms, but not for speculative-grade firms. After incorporating changes in accounting quality into the credit ratings analysis, we find no evidence that rating agencies have tightened their credit standards. Our findings underscore the critical role of accounting quality in the credit ratings analysis.

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I. INTRODUCTION

Over the latest twenty years, the average credit rating of U.S. corporations has trended down. 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. Another interpretation is that the decline in average ratings reflects *a tightening of credit standards* by agencies, implying a decreasing default probability for a given credit rating.

These two competing explanations are not easy to disentangle, even though they are not mutually exclusive. Examining a sample of *investment-grade issuers only* over the period 1978 to 1995, Blume, Lim, and MacKinlay (1998) estimate a model of credit ratings using a number of accounting and market risk variables. They interpret the annual intercept as a general measure of credit standards, after controlling for the other variables. Interestingly, they report a downward trend in the annual intercept, which they interpret as a systematic tightening of ratings standards, ceteris paribus. Indeed, the widely-quoted paper by Blume et al. (1998) has given the impression that credit ratings have become more stringent in the 1990s. Their finding appears to have influenced views on rating consistency by academics, practitioners, and regulators.[1]

This is an interesting result, but hard to explain. Why would the agencies systematically change their ratings standards? No behavioral explanation is advanced. In fact, the agencies argue that they take great pains at ensuring the consistency of their ratings process over time and across firms (Moody's, 2001). Even though agencies are beset by conflicts of interest, it is hard

[1]A search of Google Scholar indicates that Blume et al. (1998) paper has been cited by 109 studies. In terms of its regulatory impact, the paper was cited by the Federal Reserve Board in its 2001 comment letter on the proposal of *Draft Standard and Basis Conclusions-Financial Instruments and Similar Items* issued by the International Accounting Standards Committee. It was quoted also by the Federal Reserve Bank in a 2003 research report on the U.S. banking sector.

to understand why they would tighten credit standards.[2] Further, a tightening of credit standards by rating agencies, if it occurred, could undermine the usefulness of credit ratings and have an adverse impact on the cost of debt financing. For instance, for a constant sample of 137 investment-grade firms for the period of 1985 to 2002, we find that the average rating fell from A+ to A−. A drop of two notches translates into higher debt costs. For instance, in 2005, average yields would have increased from 4.98 percent to 5.23 percent, or 25 basis points. Hence, a tightening of standards would result in a significant increase in funding costs, all else equal.

This paper reexamines the causes of the observed decrease in average credit ratings. We first examine trends in default rates within each rating category using S&P's one-year default rates data from 1981 to 2003. We find no evidence that default rates have changed over time for a given credit rating, which contradicts the hypothesis of tightening credit standards.

Next, the analysis turns to the ordered probit approach, which relates the discrete ratings to a set of accounting and financial variables, as in Blume et al. We first extend the sample from investment-grade firms only to speculative-grade firms and find no evidence of a downward trend in the intercept for speculative-grade firms. This finding is *new* and important, given that nearly 40% of issuers rated by S&P are speculative grade and the proportion of speculative-grade firms has steadily increased from 26% to 46% over the period of 1985 to 2002 (see Table 1). At a minimum, tightening credit standards should be qualified by "for investment-grade issuers only." Further, this result casts doubt on the tightening explanation, as it is not clear why

[2] On the one hand, rating agencies have a financial incentive to accommodate the preferences of bond issuers from which they derive revenues. On the other hand, they have a countervailing incentive to protect their reputation for being independent and objective. Covitz and Harrison (2003) perform empirical tests of these two opposite views, and find that reputation effects dominate. None of this explains why they would tighten credit standards. If direct financial incentives are important, ratings may be too lax. If reputation effects are important, ratings need to be consistent and informative. Further, these effects have been in place since the inception of the credit rating agencies. Any tightening explanation would have to be associated with *changes* in incentives.

rating agencies would tighten standards for investment-grade firms but not speculative-grade firms.

We then examine 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 factor is the quality of accounting information. Rating agencies explicitly claim that they take into account accounting quality in their ratings analysis. This is evident in an excerpt from S&P's Corporate Ratings Criteria (2003, p. 22) below:

> *"Ratings rely on audited data, and the rating process does not entail auditing a company's financial records. Analysis of the audited financials begins with a review of accounting quality. The purpose is to determine whether ratios and statistics derived from financial statements can be used accurately to measure a company's performance and position relative to both its peer group and the largest universe of industry or utility companies."*

Interestingly, Blume et al. also acknowledge the role of accounting quality by noting the possibility that "the information content of a specific (accounting) variable itself has changed over time." They, however, do not consider accounting quality in their paper.

Recent developments of credit risk models provide theoretical underpinning for the effect of accounting information on credit risk. Specifically, Duffie and Lando (2001) show that imprecision in accounting measures of firm value increases default risk. This implies that a declining quality of accounting information would lead to greater default risk and higher debt yield spread.

We argue that accounting information may have become less reliable over time due to increased earnings management. Indeed, we show that the value-relevance of commonly used accounting ratios to *creditors* has declined and earnings management has increased over time for investment-grade firms. In contrast, we find no discernible time trend for speculative-grade firms. After incorporating accounting quality in the ratings analysis, the downward drift in the intercept of the ordered probit model disappears. The finding is consistent with our argument that changes in accounting quality explain the apparent tightening of credit standards.

It is important to note two requirements for an explanation of the downward drift to be credible. First, it must have a sound theoretical basis. Second, it needs to explain the presence of a downward drift in investment-grade ratings as well as its absence in speculative-grade ratings that we discovered in the data. The explanatory factor has to survive these two conditions.[3] We argue and show in subsequent sections that the changing accounting quality factor satisfies both conditions. Hence, it offers a credible explanation for the apparent tightening of credit standards.

We gauge accounting quality in two ways. One measure is the value-relevance of accounting ratios to credit risk analysis. This is proxied by McFadden pseudo-R-square from the ordered probit regression of credit ratings on accounting ratios. This measure is analogous to the approach commonly used in the accounting literature that measures value relevance by the R-square of a regression of stock price on earnings and book value (Brown, Lo, and Lys, 1999). Our second measure is earnings management activities. Following the extant earnings management literature (e.g., Dechow, Sloan, and Sweeney, 1995; Teoh, Welch, and Wong, 1998; Hribar and Collins, 2002), we estimate earning management by discretionary accruals based on a cross-sectional modified version of the Jones (1991) model.

[3] Our examination of common rating determinants such as market beta, idiosyncratic risk, size, leverage and profitability shows that none of these variables meets the two conditions concurrently. Hence, these variables cannot explain the downward drift in ratings. By the same token, neither can accounting conservatism, as the temporal increase in accounting conservatism, if true, should be associated with more favorable ratings over time.

Our tests also control for the increased risk of U.S. corporations (Campbell, Lettau, Malkiel, and Xu, 2001) and shifts in industry composition of the sample towards riskier segments. In subsequent sensitivity analyses, we provide cross-sectional evidence on the link between accounting quality and credit ratings and also show that our results are robust to alternative earnings management models, changes in sample composition, and inclusion of other ratings variables.

This paper makes several contributions to the accounting literature. First, we find that the apparent tightening of credit rating documented by Blume et al. (1998) can be attributed primarily to changes in accounting quality over time. Specifically, 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 degree of earnings management for these two groups. These findings, therefore, illustrate the important role of accounting quality in the credit rating process.

Second, this is the first paper to conduct a temporal analysis of the value-relevance of accounting information from the *creditors*' perspective. A recent survey paper on the accounting value-relevance studies by Holthausen and Watts (2001) notes 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." Our findings, hence, fill a gap in the value-relevance literature.

Further, we document for the first time notable temporal differences in the value-relevance of accounting information and earnings management between the investment-grade and speculative-grade firms. This is in contrast to the approach commonly taken by the value-relevance/earnings management studies that generally base their inferences on pooled samples (Brown et al., 1999; Cohen et al., 2004, Rajgopal and Venkatachalam, 2005). We demonstrate that the dichotomy into different rating groups yields new insight on earnings management activities over time.

Finally, this study contributes to the credit ratings literature. First, we show that the apparent tightening of standards reported by Blume et al. cannot be generalized to speculative-grade firms. Second, we demonstrate the critical role of accounting information in the ratings analysis. In so doing, we help clarify a widespread misconception that rating agencies have tightened their standards.

The remainder of the paper is organized as follows. Section II describes the importance of credit ratings to capital market participants. Section III discusses the role of accounting quality in credit ratings. Section IV then 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 V describes data and descriptive statistics for this model. Section VI presents empirical results and robustness checks. Section VII concludes.

II. IMPORTANCE OF CREDIT RATINGS IN CAPITAL MARKETS

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."[4] In the United States, S&P rates all public corporate debt issues over $50 million—with or without a

[4] S&P (2003).

request from the issuer. Moody's Investor Service states that its ratings now track more than $30 trillion of debt globally.[5]

Credit ratings are important for various types of market participants. Issuers use them to improve the marketability and pricing of their debt.[6] 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.[7] 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.[8] 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. This designation, which now includes four agencies, is referenced by at least 8 federal statutes, 47 federal regulations, and over 100 state laws and regulations (Covitz and Harrison, 2003).

The effect of ratings on the pricing of securities is well documented. Using a sample of 1,014 ratings changes over the 1977-1982 period, Holthausen and Leftwich (1986) report a two-day average abnormal stock return of -2.66% in response to downgrades news. Similar stock market reactions to announcements of ratings revisions are reported by Dichev and Piotroski (2001) and Hand, Holthausen and Leftwich (1992), who also find a significant price effect on bonds. Further, the informational effects of ratings changes have become more pronounced

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[5] From Moody's web site. Relative to S&P, Moody's has greater global coverage of banks (1,660 compared to 763) and industrials (3,402 vs. 2,852). See BCBS (2000).

[6] 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.

[7] 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 bond investments.

[8] Financial contracts can include "ratings triggers," which specify that lenders can demand more collateral, or request loan repayment, if the credit rating of the borrower 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.

following the enactment of regulation FD (Jorion, Liu and Shi, 2005), suggesting the growing importance of credit ratings to capital market participants.

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 SEC's 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.[9] 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.

Changes in rating criteria that do not reflect changes in underlying default 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 would create severe distortions in capital requirements.

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

To summarize, credit ratings are widely used by various market participants. The usefulness of such ratings, however, depends critically on consistency in the credit ratings standards.

III. ROLE OF ACCOUNTING QUALITY IN THE RATING PROCESS

This section examines the theoretical reasons why the quality of accounting information should matter when setting credit ratings. A significant source of information used in ratings analysis comes from corporate financial statements. For example, at the early stage of S&P's credit rating process, an issuer is typically required to supply S&P with five years of audited annual reports and the last seven interim financial statements. A critical part of the credit ratings analysis involves the assessment of the quality of accounting data and recast an issuer's financial statements. The agencies do state that "*To the extent possible, analytical adjustments are made to better portray reality.*"[10] As a result of the recent accounting scandals such as Enron and WorldCom, rating agencies have started to publish the methodologies they use to filter corporate earnings.[11]

Recent theoretical models in the credit risk literature provide support for the importance of accounting quality for evaluating credit risk. Duffie and Lando (2001), in particular, extend the Merton approach by modeling reported total assets in financial statements as imprecise estimates of true values.[12] Bond investors, who cannot observe an issuer's true assets, must instead draw inference from the available accounting reports (and other sources of information)

[10] S&P Corporate Ratings Criteria (2003), p. 22.
[11] 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."
[12] This imprecision can be modeled in other ways. For example, Giesecke (2004) models an imperfectly observed default boundary. Collin-Dufresne, Goldstein, and Helwege (2002) assume that firm values are observed with a lag.

that would bear on the issuer's credit risk. A key finding of their model is that imprecision in reported total assets leads to higher credit spreads and greater default probabilities than otherwise. In our view, the noise in accounting reports could result from deficiency in accounting standards (e.g. a major limitation of current U.S. GAAP is their inability to accurately measure intangible assets on the balance sheet), poor disclosure quality, or/and opportunistic earnings management.

Consistent with the theory, several recent studies show that lower disclosure quality is associated with higher credit spreads (e.g., Sengupta, 1998; Yu, 2005). Similarly, Francis, LaFond, Olsson and Schipper (2005) find that greater information risk, as proxied by lower accruals quality, is associated with higher debt costs.

Several recent studies suggest that the quality of accounting data may have declined over time.[13] Brown, Lo, and Lys (1999) document a systematic decrease in the value relevance of accounting information over the period 1958 to 1996, which includes the 1978-1995 Blume et al. sample. Rajgopal and Venkatachalam (2005) report a noticeable decline in earnings quality from 1962 to 2001. Cohen, Dey, and Lys (2004) document a steady increase in earnings management over the period 1987 to 2001, which they attribute in part 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 expenses and overstating sales revenues. Income can also be smoothed, which makes the firm appear less risky than it really is.

[13] In contrast, several other studies (e.g., Francis and Schipper, 1999; Landsman and Maydew, 2002) find no evidence indicating that the informativeness of financial statements has declined over time. The mixed evidence on changing accounting quality is attributable to many factors such as differences in the definitions of accounting quality, research design, and sample selection.

Leverage can be decreased through the accounting treatment of operating leases, or by hiding debt in Special Purpose Entities that enable a 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 (2005), financial executives state that they try to meet earnings benchmarks for a number of reasons, including to "achieve or preserve a desired credit rating." And this is especially the case for firms that are large and have a high credit rating, which correspond to our investment-grade sample.

In summary, to the extent that the informativeness of accounting variables has decreased and opportunistic earnings management has increased over time, the declining quality of accounting information may explain the apparent tightening of credit standards. As indicated in the introduction, this factor, however, must also explain the sharply different empirical trends for the investment-grade and speculative-grade samples, which is a stringent test.

IV. 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."[14] "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.

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

This section examines the stability of the credit ratings process by focusing on the annual default rate within each rating category.[15] 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.[16] This is the longest period for which S&P provides such data.

The number of defaults in a period can be represented by a binomial distribution. Each entry represents the average default rate in percent and is accompanied by its standard error. Take for example the 1981 entry for B-rated firms. Out of 88 firms initially B-rated at the beginning of the year, the average default rate was 2.27%, with a standard error of 1.59%.

The table shows many zero entries, implying no default within the ratings class for that year. For instance, there has not been any instance of default of AAA-rated firm 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 firms, we have one occurrence of default, out of 603 firms in 1999.[17] Over the whole sample, this translates into a 0.01% default probability, but with a standard error of 0.1%. A-rated firms also had very low default rates.

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[15] We did not use data on downgrades and upgrades because what matters is default. Some intermediate transition probabilities could be higher or lower, but ultimately the ratings measure is for the cumulative probability to default.

[16] This sample includes non-U.S. firms. We compiled this information from publicly available documents, which contained detailed information for the global sample only. Rating agencies anyway indicate that their ratings should be consistent across geographical locations. Moody's (2004), for instance, find similar loss rates across the U.S. and Europe for each rating category. Ammer and Packer (2000) report that they "do not find significant differences in default rates between US and non-US firms." S&P (2003) also states in its rating criteria that it imposes a consistent common discipline on all across-border analysis so that its ratings are comparable on a single scale. We use 1-year default rates because such choice leads to the largest number of independent observations. Using 10-year default rates would lead to basically two observations only over the period 1981 to 2003.

[17] 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

Among investment-grade firms, BBB firms 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.[18] Therefore, we will only be able to identify trends in default rates for the BBB category among investment grade firms. Likewise, the BB and B categories lead to accurate measures of default rates, because of higher default rates and large sample sizes, 9,817 and 10,046 firm-years, respectively. The CCC/C category, in contrast, has much smaller sample size, but its default rates, as expected, are the highest. Thus, tests of changes in default rates should be more powerful for the speculative-grade sample than for the investment-grade sample.

We can now examine trends in the rating standards. Tightening standards implies that for a given rating category, the default rate 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. We compare the average default rate over each period. As indicated by the entries "equality t-test," 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.

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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.

[18] We can apply the usual t-test assuming on an asymptotic normal distribution. The standard error is measured as $\sigma = \sqrt{p(1-p)/N}$, where p is the default probability, and N is the number of observations, assuming constant probability and independent observations.

Next, we estimate a regression of the annual default rate on a time trend. The entries "slope t-test" report tests of significance for the slope coefficients. Due to the lack of data for AAA- and AA-rated firms, results are meaningful only for the A-rated category or below. All the t-statistics but one are positive. This implies an increase in default rate, which is contrary to the tightening explanation. Except for the CCC/C category, however, the results are not significant.

Credit ratings, however, are supposed to represent probabilities of default over long horizons. We extended the analysis to a 5-year holding period (this analysis is unreported). Because the overlap introduces dependencies in the default rates, traditional tests do not apply. The results, however, do not suggest that default rates have been trending down. For investment-grade firms, the 5-year default rate is actually higher during the later sample period.

The conclusion from this section is that there is no evidence that default rates have changed over time, within each rating category. This contradicts the view of tightening credit standards. Admittedly, tests are less powerful for the investment-grade firms than those for the investment grade firms due to the small number of defaults for high-quality firms. The next sections provide a structural explanation for apparent changes in the credit rating process observed by Blume et al.

V. DATA AND DESCRIPTIVE STATISTICS

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.[19] Companies also need to have the required accounting variables to construct four accounting ratios used in credit

[19] This sample is comprehensive, as S&P claims that it "rates more than 99.2% of the debt obligations and preferred stock issues publicly traded in the United States." The sample consists of both active and inactive firms as of 2002.

rating models from 1985 to 2002, which is the longest sample period available as Compustat's coverage of S&P annual long-term issuer ratings begins in 1985. The accounting ratios include interest coverage, operating margin, long-term debt leverage, and total debt leverage.[20] 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, which correspond to 1,268 unique investment-grade obligors and 1,521 distinct speculative-grade obligors, respectively. 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 issuers is 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%. For investment-grade firms, the average rating has dropped from a value close to A to a value halfway between A− and BBB+. This could be interpreted as a general decrease in the credit quality of U.S. issuers, or tightening of credit standards (or both).

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

[20] 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.

beginning of the sample, the decrease in average rating could simply reflect the expanding pool of riskier 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 of financials went from 7% to 15% over this period. This structural shift is not observed among speculative-grade issuers, however. Normally, agencies 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 apparent tightening of credit standards is due in part to the increased proportion of financials. To control for the effect of changes in the sample composition, we include industry dummies in the ordered probit analysis. In addition, we will replicate our key finding with a constant sample of firms throughout the sample period.

Another factor that may affect credit ratings is increased risk of sample firms over time. This is proxied by the market model beta and residual risk.

Finally, as discussed in Section III, credit ratings may also be affected by a general decrease in the informativeness of accounting data, which is the focus of this study. We will examine these factors in the next section.

VI. EMPIRICAL ANALYSIS

As in previous research, we model the ordinal credit ratings using a set of accounting and financial variables that should proxy for risk. Obviously, the credit ratings provided by the agencies cannot be explained fully by these variables alone, otherwise there would be no rationale for their existence. Rating agencies also use other public information, such as competition in the industry, as well as private information. The ordered probit model is a simple approximation to this complex process. In our view, however, an interesting question is whether the changing quality of accounting information can account for the apparent tightening of credit standards.

6.1 Original Model

The model for credit ratings follows the specification of Blume et al, which is consistent with existing credit ratings literature (e.g., Kaplan and Urwitz (1979) and Iskandar-Datta et al. (1994)). 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.”

Recall that our ratings sample consists of firms from 1985 to 2002. Hence, firms may have similar X observations and credit ratings across years. If so, the time series of the residuals of model (1) for the same firm are autocorrelated. To correct for such correlation, we adopt robust standard errors adjusted for clustering on firms.

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),[21] (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.[22]

The financial variables include the market value of the firm, market model beta, and residual volatility. We expect a higher credit rating for firms that are larger, with a low beta, and with 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. 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, which arises over the 1985 to 1995 period overlapping with the Blume et al. study but continues afterward, gave rise to the interpretation of tightening credit standards. Holding other variables

[21] 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 $0 \leq C < 5\%$ and c1=5 otherwise; c2=C-5 for $5\% \leq C < 10\%$, c2=0 if $C < 5\%$ and c2=5 if $C \geq 10\%$; c3=C-10 for $10\% \leq C < 20\%$, c3=0 if $C < 10\%$ and c3=10 if $C \geq 20\%$; c4=C-20 for $20\% \leq C$ and 0 otherwise.

[22] 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.

in this regression constant, this implies that the estimated credit rating of firms in this sample went down over time. The trend is statistically significant. Its magnitude is also quite large. Table 4 shows that the drop in annual intercept is -1.42 over this period.

Figure 1, however, also displays the intercept for the speculative-grade sample. This shows no trend at all. Hence, the apparent tightening of credit standards is restricted to investment-grade issuers. Hence, any explanation of the trend in the intercept would also have to account for the sharply different behavior of these two rating categories.[23]

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, as in Blume et al. 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.

6.2 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.

[23] We also checked whether the difference in the trend could be due to the presence of "fallen angels," firms dropping from investment-grade to speculative-grade. This is not the case.

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.

6.3 Model with Industry, Risk, and Accounting Quality Effects

Recall that the key rating factor we examine is the quality of accounting information. This could be measured in several ways. In the context of the credit rating model, this can be measured by the McFadden pseudo-R-square of the probit ratings 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.

We re-estimate Equation (1) using the accounting explanatory variables only. Table 6 presents the annual McFadden pseudo-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.[24] This pattern, however, is not observed for speculative-grade issuers, for which there is no discernible trend.[25]

[24] The declining R-square may reflect lower weights assigned by rating agencies to the included ratios in more recent years. To the extent that reported accounting data become increasingly noisier due to more manipulation of financial reporting, then rating agencies would rationally place lower weights on the reported ratios over time.

[25] The decrease in R-square for investment-grade firms is unlikely due to the increasing sample size, because the number of firms went up even more for the speculative-grade sample.

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. 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, consistent with the theoretical prediction of Duffie and Lando (2001). 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 primarily 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 our second measure of accounting quality using *discretionary accruals,* which have been widely used by researchers as a proxy for earnings management (Kothari, 2001).

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. Another reason for our choice of the model is due to the finding that the modified-Jones model outperforms other discretionary accruals models in terms of specification and power (Dechow et al., 1995). Nonetheless, subsequent robustness checks indicate that our results are not sensitive to the choice of accruals models.

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) $j \neq i$ in the same industry in year t,

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

where TAC_{jt} is total dollar accruals, defined as income before extraordinary items (Compustat #123) minus cash flows from continuing operations (Compustat #308-Compustat #124),[26] ΔSALE_{jt} is the change in sales revenues (Compustat #12), PPE_{jt} is gross property plant and equipment (Compustat #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:

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

where ΔAR_{it} is the change in accounts receivable (Compustat #302). Discretionary accruals (DAC_{it}) for firm i in year t are calculated as total accruals minus nondiscretionary accruals:

$$\text{DAC}_{it} = \frac{\text{TAC}_{it}}{\text{TA}_{it-1}} - \text{NDAC}_{it} \tag{4}$$

As typical in the earnings management literature, we estimate separate cross-sectional models of discretionary accruals for each industry and year. Hence, this approach accounts for cross-sectional differences in industry-specific accounting rules as well as time-variation in economic conditions and accounting rules that affect total accruals (Defond and Jiambalvo,

[26]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

1994; Kasznik, 1999).[27] Note also that we use *signed* measure of discretionary accruals as we wish to capture the direction of earnings management. Similar results, however, are obtained using the absolute value of discretionary accruals.[28]

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.[29] In contrast, no discernible trend exists for the speculative-grade firms.

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

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cash equivalents (Compustat #1) plus the change in current maturities of long-term debt (Compustat #34) minus depreciation and amortization expense (Compustat #14).

[27]The rationale for separate industry estimation is that different industries have different accounting ratios and different abilities to manage earnings. The rationale for separate annual regressions is that earnings and accruals are affected by common industry shocks. A general increase in earnings management, however, will not be picked up by this method. This should bias our results toward not finding evidence of earnings management effects.

[28] Alternatively, we subtract changes in accounts receivable from changes in sales in the estimation of normal accruals (equation (2)). This modification makes little difference in our findings.

[29] It is interesting to note that 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

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 underlying economics. As a rational response, rating agencies discount the reported accounting data and assign lower ratings to accurately reflect the firms' economic reality. Moreover, to the extent that earnings management reduces accounting quality, the increased noise in accounting reports could lead to lower credit ratings, as predicted by Duffie and Lando (2001).

Furthermore, the annual intercept does not exhibit a downward trend any more. The intercept for 1985 is set at zero by construction. Afterward, some intercepts are positive, others negative, without a clear trending pattern. In Figure 6, the magnitude of the change from 1985 to 2001 is approximately 0.40, which is much less than the drop of -1.42 observed in Figure 1. Interestingly, there is no discernible pattern in the intercepts for speculative-grade firms.

Taken together, our analyses suggest that after incorporating accounting quality, we find no support for the hypothesis of tightening of credit standards, in line with our findings about default rates in Section IV.

Apparently, the increase in earnings management is most pronounced for investment-grade firms. As indicated in the Graham et al. (2005) 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 may be ascribed to a number of factors. One is higher *pressure* on investment-grade firms to meet their earnings targets. For example, Matsumoto (2002) reports that firms with higher institutional ownership, typically investment-grade firms, are more likely to manage earnings. Another factor is higher *capabilities* of investment-grade firms to manage their earnings. In its report on Engineering and Construction companies, for example,

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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.

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 to exotic financing sources, such as the notorious Special Purpose Entities 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 2005). 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.

6.4 Robustness Checks

6.4.1 Cross-Sectional Association between Discretionary Accruals and Credit Ratings

We conduct two sets of cross-sectional analyses to provide evidence on the link between discretionary accruals and credit ratings for investment-grade firms. First, we separate the investment-grade sample into the top 25% and bottom 25% sorted by signed discretionary accruals every year, and then apply the ordered probit regression in table 5 to each of the subsamples. The annual intercept of the regression model for the subsamples is plotted in Figure 7. For firms in the top-25% group (most aggressive earnings management), there is a strong downward trend in the annual intercept. For firms in the bottom 25% group (least aggressive earnings management), the trend is much less marked. A Chow test indicates that the difference between the trends for the two groups is significant at the 1% level.[30] The finding corroborates our argument that rating agencies rationally apply more stringent criteria to the firms whose reported data are contaminated by aggressive earnings management.

Second, we analyze the behavior of residuals by estimating an OLS regression instead of a probit analysis.[31] We regress credit ratings on all the ratings determinants in Table 5 (except the year dummies) in the entire investment-grade sample. We then correlate the residual ratings with discretionary accruals, and find a significantly negative association between the two (unreported). This suggests that firms with more aggressive earnings management are associated with less favorable ratings, all else being equal.

In sum, the cross-sectional evidence complements the time-series results in section 6.3. Together, this confirms our argument that the temporal decline in accounting quality offers a viable explanation to the apparent tightening of credit standards in investment-grade firms.

6.4.2 Alternative Earnings Management Models

While the modified-Jones model is arguably the most popular choice as a proxy for earnings management, it is not without controversy. We employ alternative accruals models to verify whether our results are sensitive to the choice of estimation methods. Specifically, we re-estimate discretionary accruals using the original Jones (1991) model. In addition, following Dechow et al. (2003) and Kothari et al. (2005), we extend the modified-Jones model by

[30] The slope coefficient from the regression of the annual intercept on year for the top- and bottom-25% groups is -0.09 and -0.06, respectively. To the extent that the annual intercept is auto-correlated, t-statistic from the regression is overstated. To overcome this problem, we first take the difference between the annual intercepts of the top- and bottom groups for each of the eighteen sample years (1985-2002), then regress the resulting difference variable on year. The coefficient on the difference variable is -0.3, significant at the 1% level.

[31] We use the OLS regression in place of the probit regression so that the error can be interpreted as residual rating after controlling for the common ratings determinants.

incorporating the change in accounts receivable in the estimation of normal accruals, by including the lagged value of total accruals and future sales growth, or by including return on assets to control for the effect of performance on discretionary accruals. We replicate Table 9 using each of these discretionary accruals models and obtain similar results.

Finally, we examine a totally different earnings management model, based on standard deviations of the residuals from a regression of the change in working capital on lagged, current and forward cash flow from operations. This model is first proposed by Dechow and Dichev (2002) using time-series data and later extended to the cross-sectional estimation by Francis et al. (2005). As in Francis et al. (2005, equation (1)), we estimate a proxy for accruals quality using the cross-sectional version of the Dechow and Dichev model, augmented with the variables from the modified-Jones model—PPE and change in sales revenues. The model is estimated for each of two-digit SIC industries. Firm-year estimates of accruals quality are the standard deviation of the firm's residuals over the past five years. Replication of Table 9 based on the new accruals metric does not change our conclusions.

6.4.3 Change in Sample Composition

One drawback of this analysis is that the sample size keeps expanding over time. This growth could potentially be related to the downward trend, perhaps because newly entering firms are riskier than the existing firms. Indeed, Brown and Kapadia (2007) find that the previously-reported increase in firm-specific risk can be attributed to new listings by riskier companies. Another potential confounding factor is more R&D-intensive firms entering the sample over time. To the extent that these firms have more unrecorded intangibles, the quality of their reported numbers may be lower as a result. Therefore, it is useful to control for the introduction of new firms.

To control for the effects of changes in sample composition, we create a constant sample of 137 investment-grade firms that have the required data for the period of 1985 to 2002 and keep their investment-grade status throughout this period.[32] The average rating for this sample drifts down from A+ to A−. Figure 8 then presents the intercept of the original model, which displays a marked trend down, as was the case in Figure 1. This confirms the results of the full sample. Next, we document an increasing trend in earnings management over the sample period (unreported). This is incorporated in the second line in Figure 8, which presents the intercept of the last model, with industry, risk, and earnings management effects (as in Table 9). We find no discernible pattern in the intercept. Overall, this constant sample confirms the results for the larger sample of firms.

Second, the results may be sensitive to industry effects that are not picked up in our industry dummy variables. Perhaps coefficients on the explanatory variables systematically differ across industrials, utilities, and financials. S&P, for example, reports different average leverage ratios for industrials, utilities, and financials, which reflects different patterns in risk and regulation. We repeat the analysis without financials, and then without financials and utilities. In both cases, we find that the conclusions are not changed.

6.4.4 Other Ratings Variables

As argued at the beginning of section V, the variables in the probit model are an approximation for the information used by rating agencies and hence are not complete. Examination of S&P (2003) corporate ratings criteria reveals three accounting variables that are

[32] Note that firm's R&D intensity may increase over time even for the constant sample, contributing to the drift in credit ratings. Further examination of the constant sample shows that the annual average of R&D intensity is very low, fluctuating within a narrow range of 0.016 to 0.021 over the sample period. Low R&D intensity suggests that the effect of R&D risk on credit ratings is unlikely to be large. Indeed, when we replicated our ratings analysis in the constant sample by including R&D intensity as a control variable, the coefficient on R&D intensity is not significant (p-value of 0.91) and, more importantly, our finding is little affected.

reportedly used by the credit agencies but do not appear in the previous analysis. This includes the ratio of operations funds to total debt, the ratio of operating cash flows to total debt, and the return on capital.[33] To alleviate a concern that other omitted ratings variables may explain the trend in the annual intercepts of the rating model, we add these variables in the ordered probit analysis. The results are essentially unchanged.

VII. 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, as suggested by Blume et al. If so, the same credit rating could mean different default probabilities at different point in time. A tightening of credit standards, therefore, could reduce the usefulness of ratings and affect adversely many market participants.

We revisit the issue of tightening credit standards in several ways. We first use a comprehensive S&P ratings dataset to examine changes in default rates for each rating category over time and find no evidence of tightening of credit standards. We then show that the downward drift in the intercept reported by Blume et al. does no apply to speculative-grade firms. This is an important new result, as it conflicts with the hypothesis of tightening credit standards. Further analyses of structural changes in investment-grade firms indicate that the apparent tightening of credit standards reported by Blume et al. is due primarily to changes in the accounting quality. Indeed, we find that the value-relevance of traditional accounting ratios has declined and earnings management has increased over time for investment-grade firms, but not

[33] See Standard and Poor's (2003), page 55 for a list of the accounting ratios used in its rating process. We use the 8 ratios listed, except EBITDA interest coverage because it is almost perfectly collinear with EBIT interest coverage.

for speculative-grade firms. After incorporating the changing accounting quality factor, we find no evidence for the tightening of credit ratings over time. Taken together, this study demonstrates the critical role of the quality of accounting information in the credit rating process.

We conclude with a caveat. As suggested by Blume et al., the apparent drift in the credit rating process could be explained by the possibility that "the information content of a specific (accounting) variable itself has changed over time." To be consistent with the empirical findings, however, any variable needs to satisfy two requirements: (1) the variable should have a sound theoretical basis for the downward drift, with an effect in the correct direction, and (2) its effect should arise in the investment-grade but not the speculative sample. This paper argues that accounting quality satisfies these requirements. We cannot rule out, however, the possibility of other potentially missing variables that may contribute to the downward drift in the intercept.

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Fig 1. Annual Intercept: Original Model

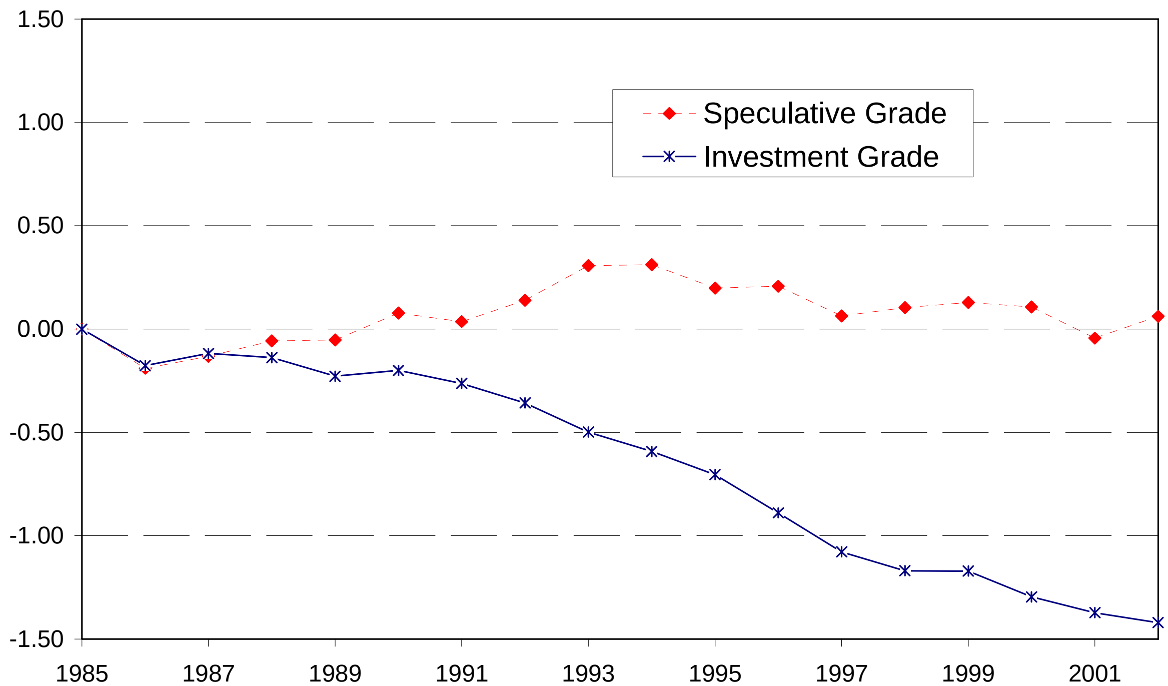

Fig 2. Annual Intercept: Model with Industry and Risk Effects

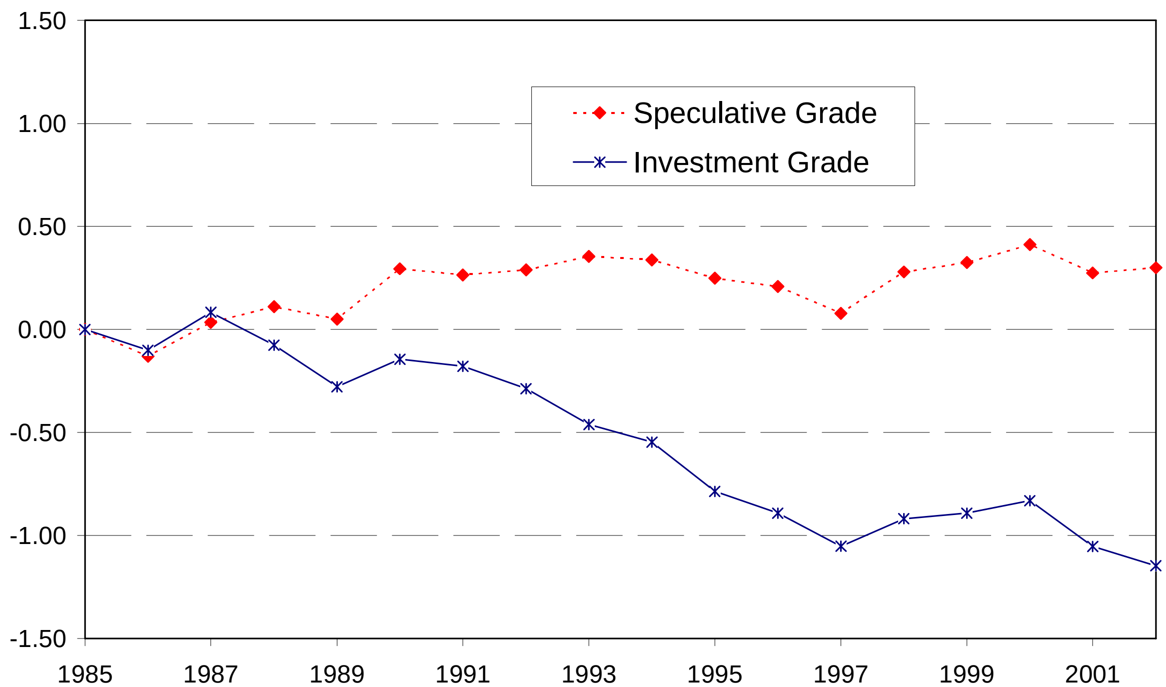

Fig 3. R-square from the Model with Accounting Data Only

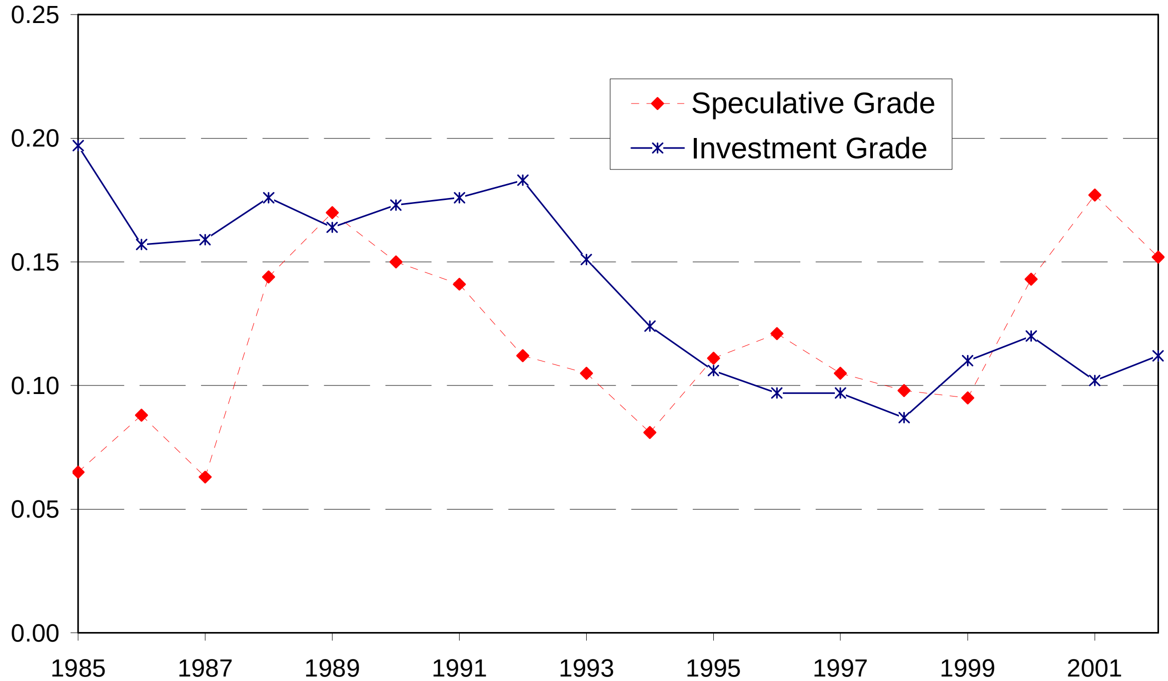

Fig 4. Annual Intercept: Model with Industry, Risk, and Accounting Quality Effects

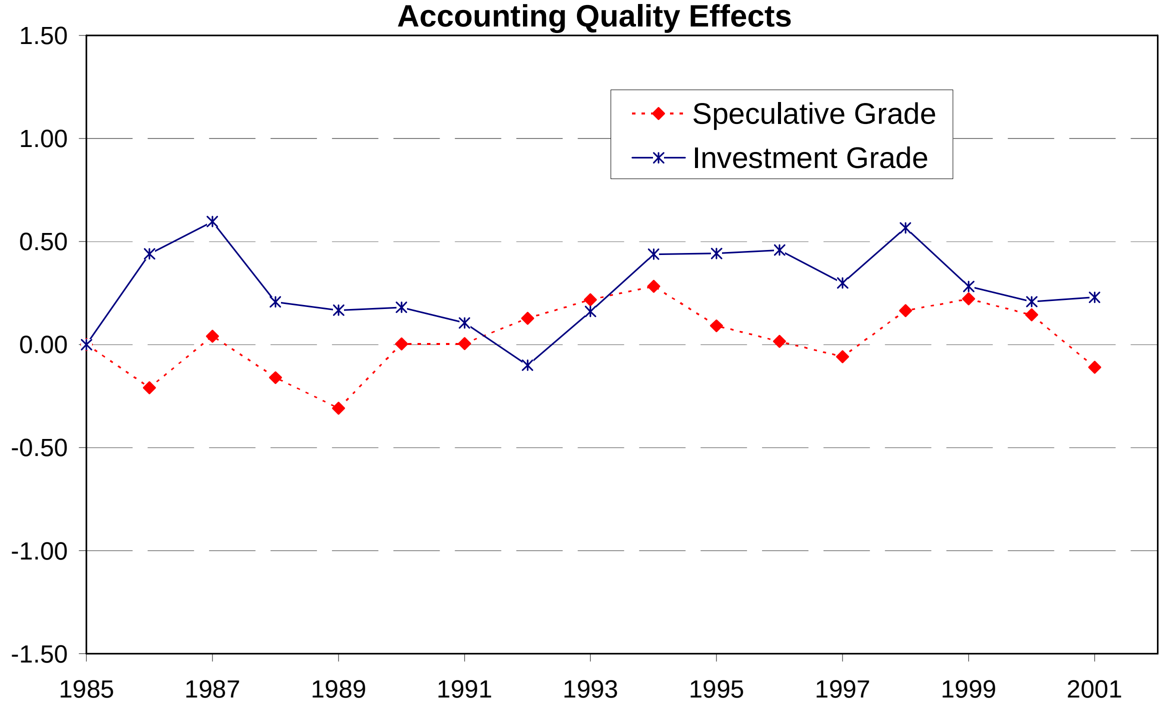

Fig 5. Earnings Management Effects Over Time

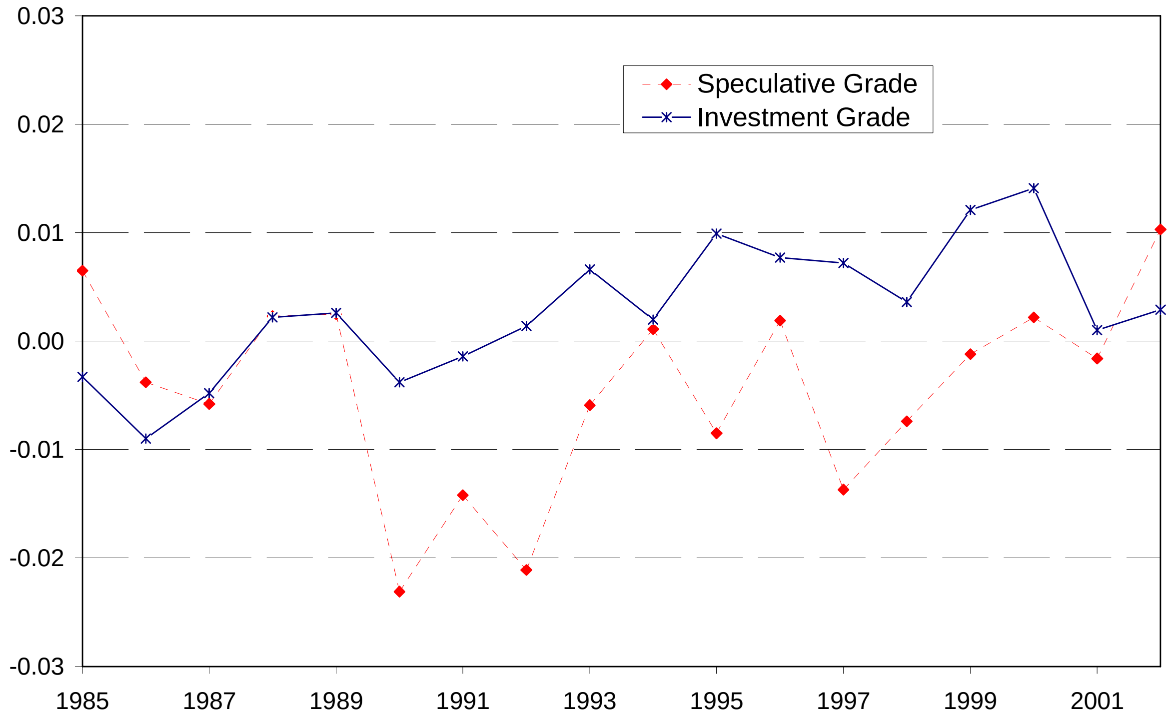

Fig 6. Annual Intercept: Model with Industry, Risk, and Earnings Management Effects

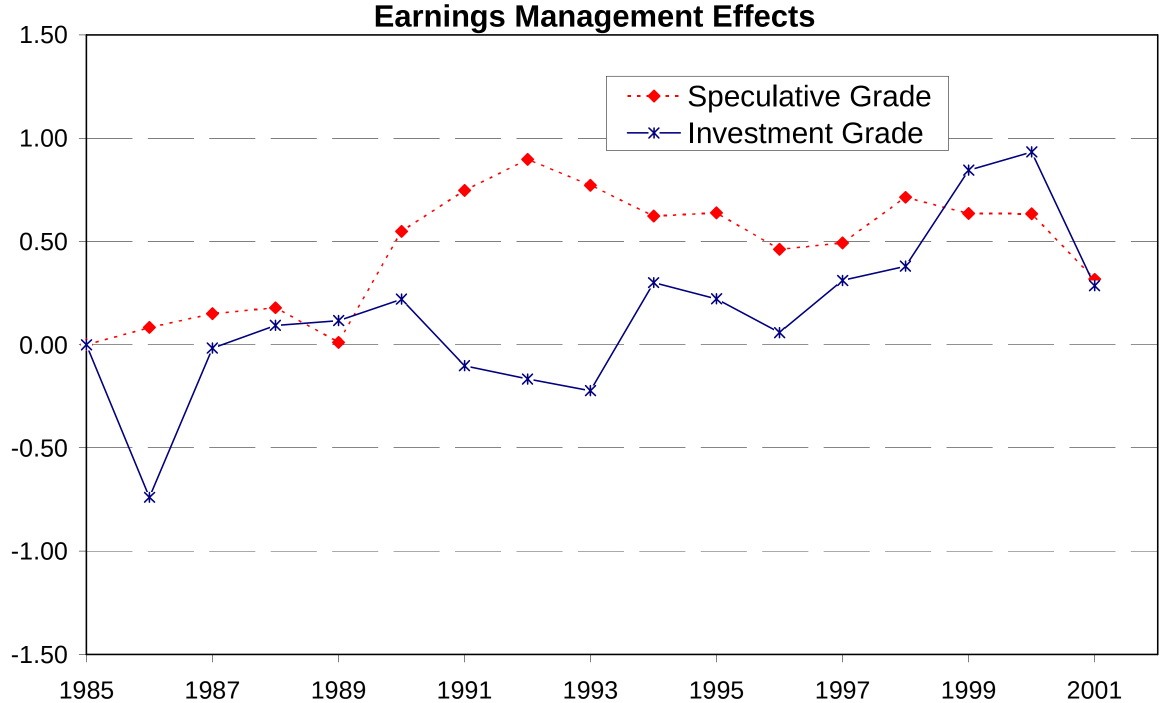

Fig 7. Annual Intercept for Investment-Grade Firms Sorted by Earnings Management

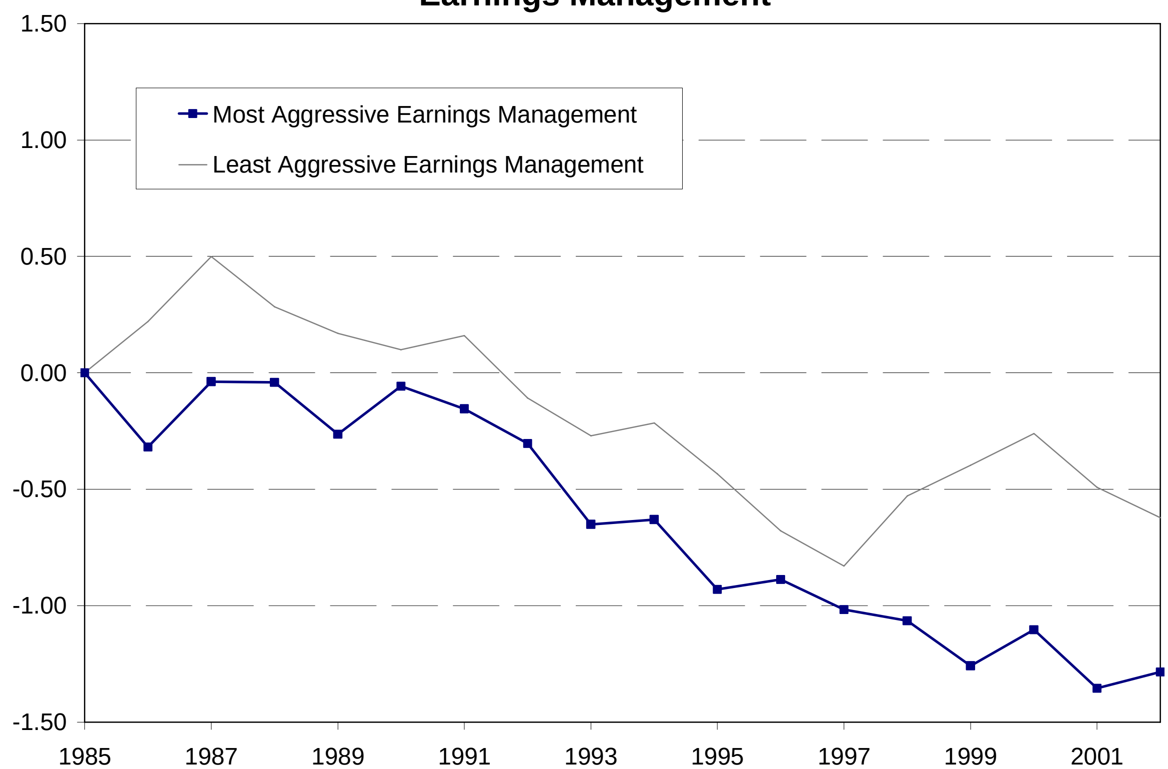

Fig 8. Annual Intercept For Constant Sample of 137 Investment-Grade Firms

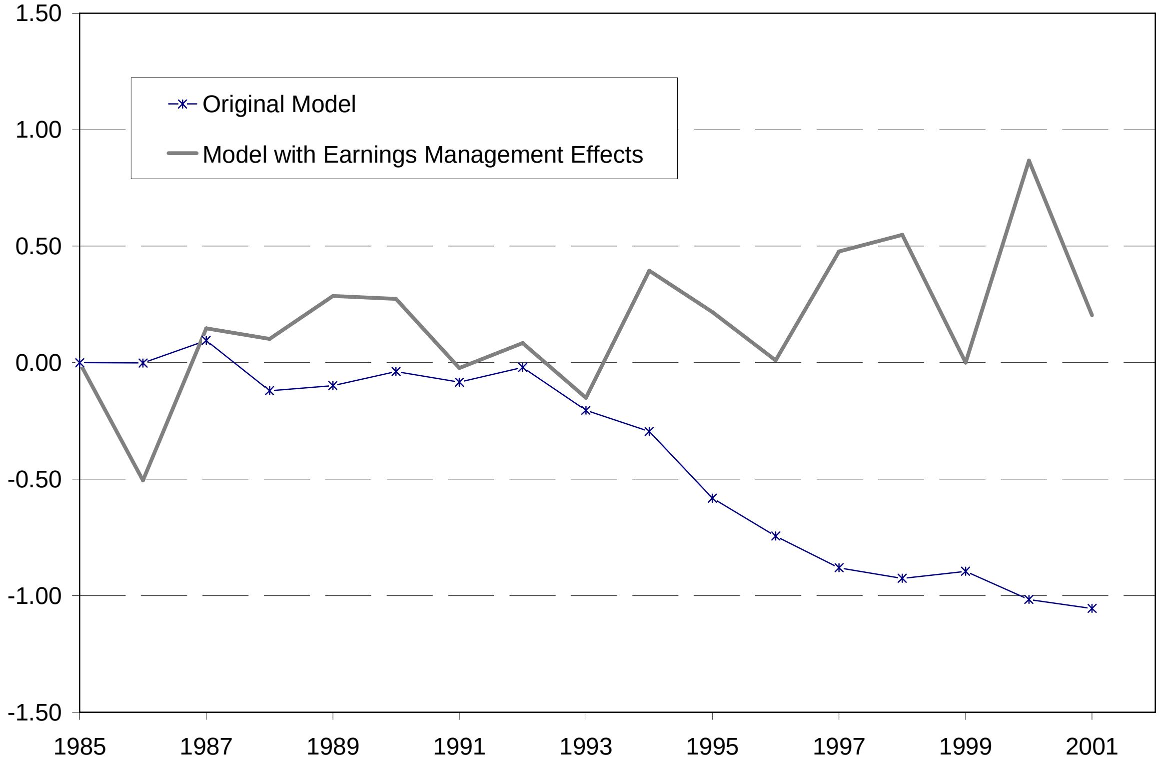

Table 1
S&P One-Year Historical Default Rates: 1981-2003
Percent (Standard Errors in Parentheses)

	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	Clustered Standard Error	P-Value	Coefficient	Clustered Standard Error	P-Value
Interest Coverage c1	0.311	0.041	0.00	0.250	0.025	0.00
Interest Coverage c2	0.020	0.019	0.27	-0.119	0.027	0.00
Interest Coverage c3	0.042	0.012	0.00	-0.004	0.018	0.81
Interest Coverage c4	-0.008	0.002	0.00	-0.001	0.003	0.86
Operating Margin	1.801	0.274	0.00	0.018	0.180	0.93
LT Debt Leverage	-4.090	0.419	0.00	0.054	0.351	0.88
Total Debt Leverage	1.128	0.326	0.00	-0.497	0.338	0.14
Market Value	0.405	0.033	0.00	0.285	0.026	0.00
Adj. Market Model Beta	-0.309	0.040	0.00	-0.124	0.035	0.00
Adj. Idiosyncratic Risk	-1.165	0.109	0.00	-0.880	0.075	0.00
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	-0.177	0.047	0.00	-0.190	0.105	0.07
1987	-0.118	0.055	0.03	-0.131	0.126	0.30
1988	-0.138	0.060	0.02	-0.057	0.129	0.66
1989	-0.228	0.063	0.00	-0.053	0.132	0.69
1990	-0.200	0.065	0.00	0.078	0.147	0.60
1991	-0.263	0.067	0.00	0.036	0.146	0.80
1992	-0.358	0.068	0.00	0.139	0.142	0.33
1993	-0.499	0.068	0.00	0.306	0.137	0.03
1994	-0.593	0.068	0.00	0.311	0.139	0.03
1995	-0.705	0.073	0.00	0.198	0.137	0.15
1996	-0.890	0.076	0.00	0.207	0.135	0.13
1997	-1.078	0.080	0.00	0.064	0.132	0.63
1998	-1.169	0.080	0.00	0.104	0.130	0.42
1999	-1.171	0.079	0.00	0.128	0.131	0.33
2000	-1.296	0.083	0.00	0.106	0.130	0.41
2001	-1.373	0.086	0.00	-0.044	0.129	0.74
2002	-1.420	0.086	0.00	0.062	0.129	0.63

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 20. 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). Clustered standard errors are robust standard errors adjusted for clustering on firms. 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	Clustered Standard Error	P-Value	Coefficient	Clustered Standard Error	P-Value
Interest Coverage c1	0.347	0.045	0.00	0.269	0.026	0.00
Interest Coverage c2	0.050	0.018	0.01	-0.132	0.028	0.00
Interest Coverage c3	0.034	0.012	0.00	-0.003	0.018	0.87
Interest Coverage c4	-0.008	0.003	0.00	-0.001	0.003	0.87
Operating Margin	1.304	0.304	0.00	-0.016	0.208	0.94
LT Debt Leverage	-4.733	0.494	0.00	0.061	0.372	0.87
Total Debt Leverage	1.412	0.340	0.00	-0.553	0.357	0.12
Market Value	0.471	0.033	0.00	0.319	0.030	0.00
Market Model Beta	-0.306	0.054	0.00	-0.152	0.039	0.00
Idiosyncratic Risk	-51.506	5.638	0.00	-16.145	3.714	0.00
Utilities Dummy	0.972	0.230	0.00	0.301	0.269	0.26
Financials Dummy	0.252	0.231	0.28	-0.482	0.251	0.06
Industrials Dummy	0.138	0.207	0.51	-0.238	0.208	0.25
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	-0.101	0.047	0.03	-0.131	0.103	0.21
1987	0.083	0.059	0.16	0.034	0.125	0.79
1988	-0.077	0.061	0.21	0.110	0.128	0.39
1989	-0.278	0.064	0.00	0.051	0.132	0.70
1990	-0.144	0.066	0.03	0.294	0.147	0.05
1991	-0.179	0.068	0.01	0.265	0.150	0.08
1992	-0.288	0.068	0.00	0.288	0.144	0.05
1993	-0.461	0.068	0.00	0.354	0.137	0.01
1994	-0.547	0.069	0.00	0.338	0.137	0.01
1995	-0.786	0.074	0.00	0.249	0.136	0.07
1996	-0.892	0.078	0.00	0.208	0.138	0.13
1997	-1.052	0.081	0.00	0.078	0.137	0.57
1998	-0.919	0.083	0.00	0.279	0.140	0.05
1999	-0.892	0.094	0.00	0.324	0.154	0.04
2000	-0.831	0.111	0.00	0.412	0.157	0.01
2001	-1.054	0.097	0.00	0.274	0.152	0.07
2002	-1.147	0.089	0.00	0.299	0.147	0.04

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 20. 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). Clustered standard errors are robust standard errors adjusted for clustering on firms. 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	0.197	(79.70)	0.065	(68.30)
1986	0.157	(77.70)	0.088	(69.40)
1987	0.159	(77.40)	0.063	(66.00)
1988	0.176	(78.70)	0.144	(74.60)
1989	0.164	(77.60)	0.170	(76.80)
1990	0.173	(77.70)	0.150	(76.90)
1991	0.176	(78.10)	0.141	(77.00)
1992	0.183	(78.10)	0.112	(72.20)
1993	0.151	(76.10)	0.105	(71.00)
1994	0.124	(73.70)	0.081	(67.30)
1995	0.106	(71.70)	0.111	(72.70)
1996	0.097	(70.80)	0.121	(73.10)
1997	0.097	(71.10)	0.105	(70.70)
1998	0.087	(69.80)	0.098	(70.40)
1999	0.110	(72.60)	0.095	(71.20)
2000	0.120	(73.80)	0.143	(75.20)
2001	0.102	(72.00)	0.177	(79.30)
2002	0.112	(72.30)	0.152	(76.50)

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. The numbers in parentheses are Percent Concordant from the corresponding yearly ordered probit regression. Likelihood Ratio Chi-Square statistic for all the yearly regressions is significant at the 0.001 level. 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	Clustered Standard Error	P-Value	Coefficient	Clustered Standard Error	P-Value
Interest Coverage c1	0.347	0.045	0.00	0.269	0.026	0.00
Interest Coverage c2	0.050	0.018	0.01	-0.132	0.028	0.00
Interest Coverage c3	0.034	0.012	0.00	-0.003	0.018	0.87
Interest Coverage c4	-0.008	0.003	0.00	-0.001	0.003	0.87
Operating Margin	1.304	0.304	0.00	-0.016	0.208	0.94
LT Debt Leverage	-4.733	0.494	0.00	0.061	0.372	0.87
Total Debt Leverage	1.412	0.340	0.00	-0.553	0.357	0.12
Market Value	0.471	0.033	0.00	0.319	0.029	0.00
Market Model Beta	-0.306	0.054	0.00	-0.152	0.039	0.00
Idiosyncratic Risk	-51.506	5.638	0.00	-16.145	3.714	0.00
Utilities Dummy	0.972	0.231	0.00	0.301	0.269	0.26
Financials Dummy	0.252	0.231	0.28	-0.482	0.251	0.06
Industrials Dummy	0.138	0.207	0.51	-0.238	0.208	0.25
Accounting Quality	13.498	1.044	0.00	3.435	1.691	0.04
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	0.439	0.050	0.00	-0.210	0.085	0.01
1987	0.597	0.055	0.00	0.041	0.128	0.75
1988	0.207	0.055	0.00	-0.161	0.102	0.12
1989	0.167	0.058	0.00	-0.310	0.147	0.03
1990	0.180	0.058	0.00	0.003	0.118	0.98
1991	0.105	0.058	0.07	0.004	0.108	0.97
1992	-0.100	0.061	0.10	0.127	0.105	0.23
1993	0.160	0.053	0.00	0.217	0.099	0.03
1994	0.438	0.064	0.00	0.283	0.119	0.02
1995	0.442	0.073	0.00	0.091	0.094	0.34
1996	0.458	0.075	0.00	0.015	0.086	0.86
1997	0.298	0.070	0.00	-0.059	0.089	0.51
1998	0.566	0.071	0.00	0.165	0.098	0.09
1999	0.282	0.058	0.00	0.221	0.113	0.05
2000	0.208	0.068	0.00	0.144	0.072	0.05
2001	0.229	0.044	0.00	-0.110	0.075	0.14

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 20. 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). Clustered standard errors are robust standard errors adjusted for clustering on firms. 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 (dollar) 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.

$$DAC_{it} = \frac{TAC_{it}}{TA_{it}} - NDAC_{it}$$

* 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	Clustered Standard Error	P-Value	Coefficient	Clustered Standard Error	P-Value
Interest Coverage c1	0.382	0.050	0.00	0.271	0.027	0.00
Interest Coverage c2	0.052	0.019	0.01	-0.135	0.029	0.00
Interest Coverage c3	0.039	0.013	0.00	-0.001	0.019	0.96
Interest Coverage c4	-0.010	0.003	0.00	-0.000	0.003	0.94
Operating Margin	1.055	0.336	0.00	-0.099	0.220	0.66
LT Debt Leverage	-4.842	0.535	0.00	0.179	0.429	0.67
Total Debt Leverage	1.654	0.352	0.00	-0.657	0.421	0.12
Market Value	0.461	0.035	0.00	0.323	0.030	0.00
Market Model Beta	-0.329	0.057	0.00	-0.168	0.041	0.00
Idiosyncratic Risk	-51.601	6.121	0.00	-15.878	3.899	0.00
Utilities Dummy	1.022	0.241	0.00	0.203	0.272	0.46
Financials Dummy	0.127	0.247	0.61	-0.698	0.262	0.01
Industrials Dummy	0.171	0.215	0.43	-0.337	0.213	0.12
Earnings Management	-115.1	9.661	0.00	22.993	11.695	0.05
Year Dummies						
1985	0.000	-	-	0.000	-	-
1986	-0.739	0.088	0.00	0.083	0.203	0.68
1987	-0.017	0.068	0.80	0.150	0.192	0.43
1988	0.093	0.063	0.14	0.179	0.167	0.29
1989	0.116	0.062	0.06	0.011	0.133	0.93
1990	0.220	0.062	0.00	0.549	0.281	0.05
1991	-0.102	0.071	0.15	0.746	0.376	0.05
1992	-0.166	0.069	0.02	0.896	0.424	0.04
1993	-0.223	0.064	0.00	0.771	0.328	0.02
1994	0.300	0.063	0.00	0.622	0.257	0.02
1995	0.222	0.070	0.00	0.638	0.306	0.04
1996	0.058	0.067	0. 39	0.461	0.254	0.07
1997	0.311	0.080	0.00	0.492	0.340	0.15
1998	0.380	0.070	0.00	0.713	0.359	0.05
1999	0.845	0.093	0.00	0.635	0.315	0.04
2000	0.933	0.094	0.00	0.633	0.265	0.02
2001	0.285	0.052	0.00	0.317	0.179	0.08

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 20. 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). Clustered standard errors are robust standard errors adjusted for clustering on firms. P-values are two-sided.