The Quality of Corporate Credit Rating: an Empirical Investigation

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Abstract

The quality of external credit ratings has scarcely been examined. The common thesis is that the rating firms' need for reputation and competitiveness in the rating industry force rating agencies to provide ratings that are efficient with respect to the information available at the time of rating. However, there are several reasons for doubting this thesis. In this paper I use survival analysis to test the quality of S&P corporate credit ratings in the years 1983-1993. Using sample data from 2631 bonds, of which 238 defaulted by 2000, I provide evidence that ratings could be improved by using publicly available information and that some categorizations of ratings were not informative. The results also suggest that ratings as outlined in S&P methodology were not fully adjusted to business cycles. The methodological contribution of this paper is the introduction of proportional hazard models as the appropriate framework for parameterizing the inherent ratings information.

Keywords: Credit Risk, Credit Rating, Corporate Bonds, Survival Analysis

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Introduction

Credit ratings are extensively used by investors, regulators and debt issuers. Most corporate bonds in the US are only issued after evaluation by a major rating agency and in the majority of cases the rating process is initiated at the issuer's request. Ratings can serve to reduce information asymmetry. Issuers willing to dissolve some of the asymmetric information risk with respect to their creditworthiness and yet not wishing to disclose private information can use rating agencies as certifiers. In such a case, ratings are supposed to convey new information to investors. Ratings can also be used as regulatory licenses that do or do not convey any new information. Contracts and regulations that have to be based on credit risk measurements have to relate to an accepted risk measurement. In such cases, ratings do not necessarily convey new information to investors and rating agencies play the role of providers of regulatory licenses.

There are several reasons for questioning the quality of the rating agencies' product. The first reason is the noisiness of the information revealed by oligopolostic certifiers. Partony (1999) claims that the growing success of rating firms is a result of higher dependence of regulators on ratings. Corporations that want their bonds to be purchased by regulated financial organizations must have them graded by one of the recognized rating firms. However the number of such firms is low due to the reputation needs and regulation by the Securities and Exchange Commission (SEC). Such barriers to entry on the one hand and the high demand by bond issuers and regulators on the other hand might have given the rating agencies excessive market power. Several theoretical studies deal with the informational disclosure strategies of monopolistic certifiers. Admati & Pfleiderer (1986) show that a non-discriminating monopolistic seller of information is reluctant to invest in gathering information. Moreover, he will also tend to produce noisy information since the more accurate the information, the faster it is reflected in the securities prices and therefore the less valuable it is for the buyer. Lizzeri (1999) shows that a monopolistic certifier does not reveal any information since it wishes to attract even the lowest types of firms. In such a case any firm refusing to pay the certifier discloses its low quality. Lizzeri also shows that competition among certifiers can lead to full information revelation.

The second reason for questioning the quality of credit rating is inconsistency due to human judgment and methodology of the rating process. Rating agencies have to assess default risks of tens of thousands of firms from hundreds of industries in dozens of countries. This job is done by numerous analysts working in separate teams. Grading the default risk of firms under such circumstances is subject to inconsistencies.

The third reason for examining ratings' quality is self-selection in bond markets. If a firm has alternative funding sources, then it might decide not to issue a new bond if the rating it receives is low. However, when such a firm gets a rating better than it expected, it would tend to issue a new bond. Such self-selection may cause ratings of new bonds to be less informative.

One other possible direction for questioning the informational revelation of ratings concerns the breadth of rating categories. Reducing the number of categories might create a situation where it is still possible to differentiate between firms within each category by using publicly available information. To illustrate, it might be that, within a credit rating category, firms with higher leverage tend to have higher default risk. [1]

Several studies try to investigate quality of ratings with respect to revelation of new information.[2] The common test in these studies is based on testing the significance of the reaction of investors to changes in ratings. Kliger and Sarig (2000), when focusing on a refinement of Moody's rating system in 1982, show that investors indeed reacted to changes in ratings as if they

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[1] In April 1982 Moody's refined its ratings by splitting each of the categories Aa, A, Baa, Ba, B into three subcategories. The fact that such a split was possible indicates that prior to the split one could use information to grade the firms within each category. Such a possibility for further differentiation might still exist.

[2] Griffin and Sanvicente (1982), Holthausen and Leftwich (1985), Hand, Holthausen and Leftwich (1992).

revealed new information.[3] However, this test is conducted on one event that does not necessarily reflect the informational content of ratings in subsequent years.

A few papers test the quality of ratings with respect to informational efficiency. These studies focus on the inconsistency question only by testing the consistency of ratings across industrial segments and geographical regions. Ammer & Packer (2000) show that in some years US financial firms got higher ratings compared to other firms with similar annual default risks.[4] Cantor et al (2001) also test the possibility of inconsistency across several groups.[5] These studies do not attempt to test the existence of any inconsistency across narrower sectors and or with respect to any firm specific variable such as size or leverage. Nor do they test the information revelation of credit ratings sub-categories.

Therefore, there is a need for more in-depth examination of the quality of ratings. In this paper I test the quality of corporate credit ratings with respect to default prediction. I test whether ratings efficiently incorporate the publicly available information at the time of rating, to what extent the rating classification is informative and whether rating classifications are consistent across industries. In such examination, I allow the rating to be informative and to convey new information to the market. However, I also test whether the rating agencies could have provided a better rating using the information available at the time of rating. This test goes beyond the empirical tests by Ammer & Packer (2000) and Cantor et al (2001) by testing the efficiency of ratings with respect to other firm characteristics and narrower industrial classifications.

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[3] For this test Kliger and Sarig use the unique event of split of Moody's ratings to subcategories in 1982. In this event, Moody's divided each of ratings Aa till B into three sub-categories such as Aa1, Aa2, Aa3…B1, B2, B3. This is a unique case in which the rating agency makes a change in rating which is not accompanied by any real economic change in the rated companies.

[4] The test deals with consistency across four groups only - US financial firms, US non-financial firms, Japanese financial firms and Japanese non-financial firms.

[5] The research has been prepared for *Moody's Investors Service* and partially tests the consistency of Moody's ratings. The test was of consistency of rating across US firms and non-US firms, banks and non-banks. Their results show that speculative grade US banks tend to have higher annual default rates compared to speculative US non-bank firms over the years 1979-1999. A comparison of US and non-US speculative grade issuers over the years 1970-1999 produced similar results - US firms had significantly higher annual default rates. However, allowing time-varying shocks to annual default rates made these differences between sectors statistically insignificant.

Credit risk is usually perceived in three different dimensions - probability of default, expected default loss and credit quality transition risk. In this study I review the methodology of the rating process used by Standard & Poor's (S&P) and show that the corporation's senior unsecured (issuer's) rating is an estimate of the firm's long-term probability of defaulting. To represent this long-term default probability I use the hazard rate - the probability of default at time t conditional on survival till time t. The empirical test is based on survival analysis using a proportional hazard model. This is the first study to use such a model to parameterize the credit rating and shows that it is a more refined approach to addressing the meaning of rating as interpreted by the rating agencies' announced guideline. This methodological innovation also enables the curse of rare events in empirical studies of defaults to be overcome, since it views cases of defaults within a long-term horizon and not within an annual horizon. Therefore, this empirical method is an improvement with respect to both addressing the real meaning of rating and overcoming the curse of rare events.

Using partial maximum likelihood, it is possible to test whether publicly available information concerning the issuer, as well as industrial and geographical classifications, is significant in explaining default hazard rate after controlling for rating. I also test to what extent the categorization in S&P rating is informative with respect to default prediction. Or in other words, I test whether ratings could be based on less rating categories without loss of relevant information.

The database used in this study is quite unique. A list of 10,000 new corporate bonds issued in the US during the years 1983-1993 is linked with the issuers' characteristics retrieved from *Compustat* and lists of default occurrences during the years 1983-2000, obtained mainly from *Moody's Investor Services* publications. After eliminating financial corporations, multiple issues by single issuers within a calendar year, and other observations with key variables missing, a database with 2631 bonds of 1033 issuers is left. The long-term horizon that features the survival analysis enables 238 cases of default by 158 firms to be identified. Therefore this methodology enables hypotheses to be tested that could not be addressed using traditional methods.

The results show that the S&P rating categorization during the sample period is not fully informative. The probabilities of default for two adjacent rating categories are not significantly different from each other. Moreover, the estimated probabilities of default do not follow the expected monotonic structure. This result is also supported by figures provided by S&P itself. However, contrary to some claims, S&P ratings not only enable a distinction to be made between investment grade firms and speculative grade firms but also to some extent within each of these two groups.

Another main result is the inefficient incorporation of publicly available information in ratings. Firm characteristics such as size, leverage, and provision of collateral and industrial classification explain default probability even after controlling for the informational content of ratings. The robustness tests show that using issuers' ratings instead of issues' ratings does not change these results. It is also shown that this additional explanatory power exists even when controlling for the full informational content of ratings (sub-categorized ratings).

The paper also attempts to examine to some extent, whether the anomalies found are consistent during the sample period and hence applicable for improving ratings. When the sample is split into two sub-samples and the estimation process repeated, it appears that the provision of collateral and leverage still retain their additional explanatory power in the same direction in both sub-samples. However, the results concerning size of the firm and industrial classification do not follow a fully consistent pattern across the two sub-samples. Hence, this exercise indicates that the firm-specific information, such as provision of collateral and leverage, were not efficiently incorporated in the assignment of ratings. It cannot be ruled out that the explanatory power of industrial classification after controlling for rating is due to shocks that were correlated with the classification only ex-post.

It is also shown that when testing the significance of publicly available information after controlling for informational content of ratings, the narrower the definition of industrial classification, the more significant the variables such as size and leverage. Or in other words, the more exact the controlling for industrial classification, the more significant the additional explanatory power of size and leverage. This pattern supports the thesis that rating agencies fail to correctly incorporate the heterogeneous interpretation of such variables across industries.

The remainder of the paper is organized as follows. In Section I, I review the rating industry and rating process. Section II describes the methodology used. Section III describes the data and Section IV the results. Section V contains the conclusions.

I. Rating industry and rating process

The main bond rating agencies in the United States are *Moody's Investors Service* (Moody's) and *Standard and Poor's* (S&P). Since the mid-1980s there has been a tremendous increase in rating activity.[6] In the 1980s S&P and Moody's employed only few dozen whereas today they employ thousands. Moody's annual revenue reached $600 million in year 2000, of which more than 90% was derived from bond rating, and its total assets amounts to $300 million. Moody's financial results reveal high profitability with annual net income in 2000 reaching $158 million (52.8% of its total assets).

A rating, according to rating agencies definition, is an opinion on the creditworthiness of an obligor with respect to a particular debt. In other words, the rating is designed to measure the risk of a debtor defaulting on a debt. Both Moody's and S&P rate all public issues of corporate debt in excess of a certain amount ($50 million), with or without issuer's request. However, most

[6] See White (2001) for details.

issuers (95%) request the rating. The rating fees are based on the size of the issue and not on any known characteristic of the issuer. These fees are relatively small compared to the size of issues.[7]

When an issuer requests a rating for its issue, S&P assigns a special committee and a lead analyst to assess the default risk of the issuer before assessing the default risk of the issue itself.[8] The committee meets the management for a review of key factors affecting the rating, including operating and financial plans and management policies. Following the review, the rating committee meets again and discusses the analyst's recommendation. The committee votes on the recommendation and the issuer is notified of the decision and the major considerations. The S&P rating can be appealed prior to publication if meaningful additional information is presented by the issuer. The rating is published unless the company has publication rights, such as in a private placement. All public ratings are monitored on an ongoing basis. It is common to schedule an annual review with management. Ratings are often changed.

The main factors considered in assigning a rating are: industry risk (e.g. each industry has an upper limit rating – no issuer can have a higher rating regardless of how conservative its financial posture); size - usually provides a measure of diversification and market power; management skills; profitability; capital structure; cash flow and others. For foreign companies, the aggregate risk of the country is also considered. In particular, foreign companies are usually assigned a lower rating than their governments - the most creditworthy entity in a country.

S&P uses ten rating categories, AAA to D while Moody's uses nine categories, from Aaa to C. Both agencies divide each of the categories from AA (Aa) to B into three subcategories; e.g. AA category (Aa of Moody’s) is divided into three subcategories – AA+ (Aa3), AA (Aa2) and AA- (Aa1). Portfolio managers are required by regulators or executives not to hold 'speculative bonds'. It is common practice to use credit ratings to define such bonds. Bonds with rating 'BBB'

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[7] S&P charges amounts of $25,000 up to $125,000 on issues up to $500 million and up to $200,000 on issues above $500 million. Rates are negotiable for frequent issuers.
[8] Since the empirical test is based on S&P ratings, the methodology presented is of S&P. Moody's rating methodology is quite similar.

or 'Baa' and higher are called 'investment bonds' and bonds with lower ratings are called 'speculative bonds' or 'junk bonds'. Therefore, from the perspective of some bond issuer, reaching grade of 'BBB' or 'Baa' is a crucial minimum.

After assigning a rating to the issuer, the rating agency assigns ratings to its issues on the same scale. The practice of differentiating issues of the same issuer is known as notching. Notching takes into account the degree of confidence with respect to recovery in case of default. The main factors considered at this stage are seniority of the debt and collateral. Notching would be more significant the higher the probability of default of the issuer. For example, a very well secured bond will be rated one notch (subcategory) above a corporate rating for investment grade categories and two notches in the case of speculative grade categories.

One important fact about rating is that neither the issue's rating nor the issuer's rating changes over time unless a fundamental change has occurred to the likelihood of payment by the company. Therefore, rating cannot be interpreted as being simple prediction of default. Otherwise the shorter the time to maturity of a bond, the higher its rating would be. Because ratings do not change, as the bond gets closer to its maturity date, it is reasonable to assume that a rating is an estimate of a company's specific default risk, regardless of the time horizon. Survival literature offers a suitable framework for analysis as it focuses on the determinants of a 'hazard rate' - the probability of default of the company at time t conditional on survival until till time t. If hazard rate is constant over time, the rating can be interpreted as being an estimate of this rate. In a more general case, where hazard rate is not constant, the rating can be interpreted as an estimate of a company's inherent default risk (that affects its hazard rate for any time horizon time t).

II. Methodology

A. Framework

Many firms issue bonds annually and some even issue multiple bonds concurrently. Let t denote one of these times in which a firm i issues a new bond. At this time the rating agency examines the creditworthiness of the firm and assigns a grade G_{it} to the firm. This rating is intended to indicate the general risk of firm i defaulting on any type of debt at anytime in the future. This rating is based on all information available at time t irrespective of the characteristics of the bond itself (especially ignoring the time to maturity). Then the rating agency examines the protections offered to the new bondholders and carries out 'notching' (as described in section I). If the bond is very well secured it may get a rating G_{it}^{B}, that is 1-2 grades (in subcategory terms) better than that assigned to the firm itself - G_{it}. And if it is subordinated it may get a rating G_{it}^{B} which is 1-2 grades lower than that assigned to the firm. G_{it}^{B} is also independent of other characteristics of the bond such as time to maturity, rate of coupon, size of issue and others.

For the purpose of testing quality of rating with respect to default probability, it would be best to have a dataset and a methodology based on firms' ratings. However, since the data on firms' ratings is not complete and might cause problems of self-selection, the methodology is tailored for a database on issues' ratings (bonds' ratings). To do this, I first describe the nature, i.e. the stochastic default process, and then I describe how issuers' ratings and issues' ratings relate to the fundamentals of this process. Then I show how, within this framework, it is possible to use the available database to test the quality of ratings.

B. Distribution of Default Occurrence

Assume that all firms that are exposed to default risk experience default at some time in the future, or in other words, default is just a matter of time. This assumption does not contradict historical experience. Firms with the highest ratings (AAA) have deteriorated over time to default. Let T_{it}^{D} be the time from t till the first time the firm i defaults.[9]

Suppose the time T_{it}^{D} has a continuous probability density $f(T;x_{it},t)$ where T is a realization of T_{it}^{D} and x_{it} is a vector of characteristics of firm i at the time of rating t. The probability distribution of T_{it}^{D} for a single firm i may change over time because of several reasons. First, the firm's characteristics x_{it} may change over time and hence cause a change in the probability distribution.[10] Second, a change in probability distribution can also occur due to macroeconomic factors, and therefore a firm with the same characteristics $x_{it} = x_{i\,t-1}$ may have different probability distributions at times t and $t-1$.

The cumulative probability of T_{it}^{D} is:

$$F(T;x_{it},t) = \Pr(T_{it}^{D} \leq T) = \int_{0}^{T} f(s;x_{it},t)ds\ , \tag{1}$$

The survival probability function is:

$$\overline{F}(T;x_{it},t) = \Pr(T_{it}^{D} > T) = 1 - F(T;x_{it},t)\ . \tag{2}$$

The hazard rate, $\theta(T;x_{it},t)$, is the probability that default occurs at time T, given that it had not occurred before T:

[9] A firm defaults if it is not able to pay interest or par of any outstanding bond. When a firms defaults on one bond, it does so on all its outstanding bonds. Therefore, any outstanding bond at time t defaults if and only if its time to maturity is greater than T_{it}^{D}.

[10] In fact, only unexpected changes of firm's characteristics can change the probability distribution, since any affect of expected change in x_{it} is already incorporated in the probability distribution of T_{it} at time t.

$$\theta(T;x_{it},t) = \frac{f(T;x_{it},t)}{\overline{F}(T;x_{it},t)}. \qquad (3)$$

θ, f and F are alternative ways of describing the same probability distribution of default. However, it is common to use θ to describe the distribution.

The hazard rate may have a term structure over T. It can be argued that *ceterus paribus* the hazard rate five years after issuing the new bond has to be different from that in the year following the new issue. For example, the flow of cash into the firm may cause its hazard rate to be low in the first years following the new issue and then to increase when the cash runs out. In such a case, the hazard rate should have an increasing pattern over time T, possibly converging to some upper bound. Following this argument, if the firm issues new bonds from time to time, one can expect the hazard rate to increase over time and then decrease whenever new debt is issued. Yet, it is also possible to rationalize decreasing hazard rate. For example, if a firm gains a positive reputation merely by surviving, which translates into lower probability. The historical evidence of the average hazard rate's term structure reveals that it first increases over time and then decreases. Moreover, it appears that the term structure of the average hazard rate depends on the level of default risk itself; the riskier the issuer/issue (the lower its rating), the faster its hazard rate reaches the maximum and starts to decrease. However it cannot be ruled out that these results are due to the unobserved heterogeneity that exists in each rating category. Moreover, when assigning a rating to a firm, rating agencies assure that its rating will not change unless there is a fundamental change in the firm's profile. Combining the fact that the assigned rating has no time horizon perspective (except, that is, long term), it can be concluded that the rating agencies ignore the term structure of the hazard rate and hence they also ignore the possibility that this term structure depends on the level of default risk. For a more detailed examination of this issue (historical evidence of hazard rate' term structure) see Appendix A.

C. Proportional Hazard Rate

For a constant hazard rate, the hazard function is denoted $\theta(T;x_{it},t)=k(x_{it},t)$ and the survival probability function is $\overline{F}(T;x_{it},t)=e^{-k(x_{it},t)T}$ which is the exponential distribution function. The hazard rate may change monotonically over time. Such a case can be represented by the Weibull distribution with $\theta(T;x_{it},t)=k(x_{it},t)aT^{a-1}$ as the hazard rate function. If $a>1$, then θ is increasing over time, and If $0<a<1$ it is decreasing over time. If $a=1$ the hazard function is constant over time and the Weibull distribution has an exponential form.

Both the exponential and Weibull distributions, as well as most of the common distributions used in survival analysis, are special cases of the proportional hazard distribution, for which the hazard rate is of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. For the exponential distribution $k_2(T)=1$, and for the Weibull distribution $k_2(T)=aT^{a-1}$. This structure assumes that the hazard rate function is separable – i.e. the term structure of the hazard rate $k_2(T)$ is unconditional on the firm's specific component $k(x_{it},t)$. Cox (1972) points out that it is possible to estimate the parameters of $k(x_{it},t)$ without specifying the form of the baseline hazard function $k_2(T)$ and therefore, this structure is very helpful. The proportional hazard rate suits the objectives of this test and the Cox nonparametric approach is adopted for the estimation process.

D. Rating Process

It is assumed that the rating agency provides an estimate of $k_{it}\equiv k(x_{it},t)$ for each firm i at each time t. [11] After estimating k_{it} the rating agency publishes a grade G_{it} on a scale of 1 to n using the following algorithm,

[11] According to S&P methodology, ratings are not fully adjusted to business cycles. Therefore the definition of the target parameter for rating agencies should have been $k(x_{it},\cdot)$. However assuming that the

$$G_{it} = \begin{cases} 1 & if \quad -\infty \le \ln \tilde{k}_{it} \le c_1 \\ 2 & if \quad c_1 < \ln \tilde{k}_{it} \le c_2 \\ . & \\ . & \\ n & if \quad c_{n-1} < \ln \tilde{k}_{it} \le \infty \end{cases} , \tag{4}$$

where $\tilde{k}_{it}$ is the rating agency's estimate for k_{it} and $C = (c_1, c_2, ..., c_{n-1})$ is a set of $n-1$ cutoff points chosen by the rating agency. G_{it} is a rating assigned to the firm itself. Then a rating G_{it}^B is assigned to the new bond issued by the firm. When assigning a rating to a new bond, the rating agency also considers collaterals provided for the bond itself, which cause the expected default loss of the bondholders to decrease should default occur. Therefore, $G_{it}^B = G_{it} + notch(collateral)$ where $notch(\ .\ ) \in \{0, -1, 1, -2, 2\}$ is the function that represents the notching process as described in section I.

We may question whether the rating G_{it} is a sufficient statistic for k_{it} conditional on the information x_{it} and time t. If not, a better estimate for k_{it} can be achieved by combining G_{it} and x_{it}. This does not mean that a better estimate can be achieved by using publicly available information only, as rating agencies can also rely on information that is not publicly available. In such a case, using publicly available information only would not necessarily lead to a better estimate of k_{it}. The objective of this paper is to test whether a combination of rating G_{it}, or in fact G_{it}^B as a proxy for G_{it}, with publicly available data could improve the estimate for k_{it}.

E. Estimation

The estimation follows survival analysis. In such a framework, the hazard rate of default or equivalently the time to default T_{it}^D is the dependent variable. First, the hazard function has to

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rating agency tries to estimate $k(x_{it}, t)$ enables us to test S&P's claims by estimating the parameters of t in $k(x_{it}, t)$.

be described. As mentioned above, the hazard function is assumed to be proportional - $\theta(T;x_{it},t)=k(x_{it},t)k_2(T)$. The firm's specific default risk component $k_{it}=k(x_{it},t)$ is formed as follows,

$$\ln k_{it} = g_{it}'\beta_g + SECURED_{it}\cdot\beta_{\mathrm{sec}ured} + x_{it}'\beta_x + \tau'\beta_\tau \qquad (5)$$

G_{it}^B and t which are discrete variables are transformed into sets of dummy variables. Formally, $g_{it}=(g_{1,it},g_{2,it},\ldots,g_{n-1,it})$ where $g_{j,it}=1$ if $G_{it}^B=j$ and $g_{j,it}=0$ otherwise and $\tau=(\tau_1,\tau_2,...,\tau_{H-1})$ where $\tau_h=1$ if $t=h$ and $\tau_h=0$ otherwise (H is the total number of years that new ratings were released in the sample).[12] $SECURED_{it}$ is a dummy variable that indicates whether the bond whose rating is used for the observation was secured by a collateral. In such a case $G_{it}^B\neq G_{it}$ and therefore, to calculate the default hazard risk, the affects of notching should be deducted by adding the variable $SECURED_{it}$. However, providing collateral might also serve as a signal for the firm's quality as described in Bester (1985). Hence, this dummy variable can be a control for both the notching effect and the signaling. x_{it} is a vector of firm's specific variables at the time of rating assignment. β_g, β_x, $\beta_{\mathrm{sec}ured}$ and β_τ are vectors of the corresponding parameters. It is not necessary to determine a source of noise in this equation because the left hand side variable of this equation determines the probability distribution itself. k_{it} is assumed to be deterministic.

Let T_{it} be the continuous period the firm i is observed in the sample to have been exposed to default risk since the issue of the new bond at time t. The end of each period T_{it} can be caused either by default or censorship. Censorship occurs if T_{it}^D is not realized (no default has

[12] For example if $G_{it}^B\in\{1,2,3\}$, then for $G_{it}^B=1$ $g_{it}=(1\ \ 0\ \ 0)$, for $G_{it}^B=2$ $g_{it}=(0\ \ 1\ \ 0)$ and for $G_{it}^B=3$ $g_{it}=(0\ \ 0\ \ 1)$.

occurred during the period T_{it}). In other words, an observation is censored if $T_{it} < T_{it}^{D}$ and uncensored if $T_{it} = T_{it}^{D}$. Then, for each observation it can be defined,

$$s_{it} = \begin{cases} 1 & if \quad default \quad \left(T_{it} = T_{it}^{D}\right) \\ 0 & if \quad censorship\left(T_{it} < T_{it}^{D}\right) \end{cases}. \tag{6}$$

Note that each observation is of one S&P rating $g_{j,it}$ assigned to the first new bond issued by firm i at year t, the period T_{it}, and the characteristics of the firm at the time of rating - x_{it}. Since the empirical test is cross-sectional, for ease of notation it would be simpler to denote each observation of the bond's rating of firm i at year t as an observation j, and the variables T_{it}^{D}, T_{it}, x_{it}, s_{it} would be notated T_{j}^{D}, T_{j}, x_{j} and s_{j} respectively.

The estimation of equation (5) is possible by adopting the partial likelihood apprach as introduced by Cox (1972). Consider an uncensored observation with the time to default T_{it}. The pratial lieklihood of this observation can be calculated by deviding its hazard rate to default at the end of period T_{it} by the sum of hazard rates at this point (T_{it}) of all firms that were exposed to default udring the whole period T_{it}. The construction of the partial likelihood PL_{j} for observation j is as follows,

$$\begin{aligned} PL_{j} &= \frac{\theta(T_{j}, x_{j}, t)}{\sum_{l} Q_{j,l}\theta(T_{j}, x_{l}, v)} = \frac{k(T_{j})}{k(T_{j})} \cdot \frac{k_{j}}{\sum_{l} Q_{j,l} k_{l}} = \frac{k_{j}}{\sum_{l} Q_{j,l} k_{l}} \\ &= \frac{\exp(g_{j}'\beta_{g} + SECURED_{j} \cdot \beta_{\mathrm{secured}} + x_{j}'\beta_{x} + \tau'\beta_{\tau})}{\sum_{l} Q_{j,l} \exp(g_{l}'\beta_{g} + SECURED_{l} \cdot \beta_{\mathrm{secured}} + x_{l}'\beta_{x} + \nu'\beta_{\tau})} \end{aligned} \tag{7}$$

where $Q_{j,l} = 1$ if $T_{l} \geq T_{j}$ and $Q_{j,l} = 0$ otherwise (The Qs enable to include in the denominator, firms that were subject to default risk during T_{j}). Since the baseline hazard function $k_2(T)$ is equal for all firms, it is canceled out from the calcualtion of the partial likelihood. The partial likelihood of the sample function can be formed:

$$PL(\beta_g, \beta_{\sec ured}, \beta_x, \beta_\tau) = \prod_i \left(\frac{\exp(g_j{}'\beta_g + SECURED_j \cdot \beta_{\sec ured} + x_j{}'\beta_x + \tau'\beta_\tau)}{\sum_{l=1}^{m_j} Q_{j,l} \exp(g_l{}'\beta_g + SECURED_l \cdot \beta_{\sec ured} + x_l{}'\beta_x + \nu'\beta_\tau)} \right)^{s_j} \tag{8}$$

Note that the partial likelihood of the sample is the multiplication of the partial likelihood of the defaulted firms only ($s_j = 1$). However this partial likelihood is not biased since the likelihood for each uncensored observation PL_j is its hazard rate to default relative to all other observations that were exposed to default risk during the period T_j, whether censored observations or uncensored. Therefore, there is no problem of selection-bias with this respect. This is one of the novelties of the method introduced by Cox (1972).

Now equation (5) and its parameters $\beta_g, \beta_x, \beta_{\sec ured}$ and β_τ can be estimated using the Maximum Likelihood procedure. Clustering is used to correct the standard error estimates of the coefficients for bias that might be caused due to multiple observations of companies in different years.

III. Data

A. Database

The database for the study was created by combining data from three main sources. A list of more than 10,000 corporate bonds issued during the years 1983-1993 was obtained from the *Capital Division of Federal Reserve*.[13] Each issue in this database is detailed with name of issuer, date of issue, S&P and Moody's rating at date of issue and other characteristics of the bond. The financial statement data, SIC classification, country of incorporation and S&P unsecured senior debt ratings were obtained from *Compustat*. A list of default events was mainly obtained from *Moody's Investor's Service* publications.

After combining all these sources and eliminating financial corporations, multiple issues within each year, companies with no S&P rating and companies that could not be linked to Compustat, 2631 bonds of 1033 non-financial corporations remained. Of which 238 bonds belong to 158 firms that default at some point after appearance of their issues in the sample. Many corporations issued more than one bond during the sample period.

Using observations with data on senior unsecured S&P rating would limit the database to 2487 issues (176 defaulted) of 861 companies (106 defaulted). Therefore being attached to direct issuer rating (senior unsecured rating) instead of issue’s rating would not only significantly decrease the number of observations but also create a biased sample. This is due to the fact that the rate of defaulted companies with no issuer rating is much higher than its proportion in population. Using issue's rating instead of issuer's rating imposes special considerations on the estimation, as it is described in section II.

[13] This dataset is used by Guedes & Opler (1996) and is in the public domain.

B. Data Definition

First, T_{it} the time that firm i has been exposed to default risk since time t is calculated. This period depends not only on the time to maturity of a bond issued at time t but also on bonds issued before and after time t. For example, if the time of maturity of a bond issued at time $t-1$ is year 1999 and the time of maturity of the bond issued at time t is 1998, then it is clear that the firm has been exposed to default risk since $t-1$ through time t till 1999. Therefore, if a firm had two or more issues with some overlapping period (from date of issue to date of maturity), then the period of exposure to default risk for each observation at time t was calculated from t till the latest maturity date. If the firm defaulted during this period then the final period T_{it} was calculated from its date of issue till date of default. In such a case (and only in such case) the observation is considered to be uncensored ($s_i = 1$). For all observations, where the period of exposure to default risk has not ended with default, the observation is considered to be censored ($s_i = 0$). An observation is also considered censored if the time of exposure to risk is beyond year 2000. The reason for that is that it is not known at what exact time (after year 2000) the firm defaults. For a thorough description of T_{it} and several examples see appendix B.

Companies' specific variables are chosen in accordance with empirical bankruptcy prediction literature. The variables are based on the first quarterly or annual financial statements published following the issue and do not rely on market data. Using data from financial statements prior to issue would ignore the changes that could occur due to the issue itself, such as changes in leverage and total assets.

Size appears to be the most significant variable in multivariate prediction of default. The bigger the firm, the more diversified its assets and therefore the lower its default risk. *Size* is calculated as $\ln(\mathit{Total\ Assets})$ to enable diminishing return to scale in respect of diversification. *Quick ratio* ([*Current Assets – Inventories*]/*Current Liabilities*) is a proxy for liquidity of the firm. The more liquid assets a firm has, the lower its propensity to default in the short term.

However survival analysis is based on measures of long term default propensity. Hence, it is not clear whether this variable should be significant. *Leverage* is calculated as (*Total Liabilities/Total Assets*). The higher the leverage, the higher the firm's exposure to default risk and its propensity to default. *Profitability* is calculated as (*EBIT/Total Assets*). The more profitable the firm, the more resources it has to pay debtors, and the lower its propensity to default. *Secured* is a dummy variable that indicates whether the company could provide some kind of collateral for its bond (such as First Mortgage, Equipment Trust or other).

Firms are also exposed to the macro-economic risks of their economies and this factor is also considered by rating agencies. The US economy is considered to be one of the most stable economies. Hence, a dummy variable was used to indicate whether the company was incorporated outside the US. Exposure to industrial risk, which is also considered in the rating process, is expressed by dummy variables indicating the industrial classification according to standardized industrial classification (SIC).

The ratings observations are taken over 11 years (1983-1993). Some firms appear in the sample several times since they issued new bonds in several different years, while other firms only appear in the sample once. Since rating is supposed to incorporate all relevant information at any time of observation, it is possible to treat multiple observations of firms separately and test whether ratings are efficient at any time. Therefore even though the sample includes multiple observations on some firms, a cross section analysis is adopted. Yet, I use clustering to calculate the standard deviation of coefficients to correct the bias that might occur due to multiple observations of firms.

Dummy variables are used for each of the years 1983 till 1992 (year 1993 is the benchmark). These dummy variables are proxies for the macroeconomic factors that affect default risks and they also solve other fundamental and econometric problems. There may be some correlation between some variables and the macroeconomic state. Suppose in 'bad years' only large *Size* firms issue new bonds. The correlation between *Size* and 'bad years' would cause biased estimators for *Size* and misinterpretation of the results. Rating categorization may also have changed during the sample period.[14] Using these dummy variables for year of issue can answer these two possible cases.

C. Data Description

Table I shows the distribution of the sample across main rating categories and observation of default. As can be seen, 851 (32.3%) of the bonds were speculative graded and 193 of those speculative bonds belonged to firms that defaulted later. Out of the 238 default observations, 193 (81.1%) belonged to firms that issued speculative bonds. The high rate of speculative bonds, as well as the adoption of the hazard model structure leads to the result of 9 percent of defaults among the bond observations and 15.3 percent among the firms. These high default rates in the sample enable investigation of the default stochastic process. It can also be seen that the lower the rating the higher the rate of defaults. In this respect, the sample seems to answer the expectations.

The rate of bonds graded BB is quite small. This may be a result of self-selection, i.e. firms which were graded very close to 'investment grade' might wait for a better time for issuing a new bond or seek cheaper sources of funding. Another explanation might be a rating agency's interest not to grade companies close to the hedge to avoid a 'bad taste'.[15] The distribution of the issuers shows the same patterns as the distribution of the bonds.

Insert Table I about here

[14] See Blume, Lim & Mackinlay (1998).

[15] A parallel example of such consideration is grading in schools. Do teachers avoid 'failure' grades that are too close to 'pass'?

Table II shows the distribution of the sample across rating subcategories. As can be seen, each rating category which is subcategorized is indeed quite spread across its subcategories and the sample includes cases of default within each sub-category.

Insert Table II about here

Table III describes the one-digit Standardized Industrial Classification (one digit SIC) of the sample. These industrial groups are quite large and each includes many cases of default. However great heterogeneity can be expected in each of these groups with respect to default risk. Therefore the statistical tests will also try to address narrower industrial classification.

Insert Table III about here

Table IV shows the industrial classification of the sample when the industries ‘Manufacturing & Equipment’ and ‘Public utilities’ are sub classified using two-digit SIC. Table V-a shows a more refined industrial classification – using two-digit SIC. Each industrial classification consists of at least 15 firms and 19 observations (bonds). All other industries that have not reached these numbers are gathered in a group called ‘other’. Table V-b describes the industrial classifications of these industries. The rate of cases of default in this group (19.5 percent of the bonds and 26.3 percent of the firms) is greater than that of the sample (9.0 percent of the bonds and 15.3 percent of the firms). These numbers indicate that the default risk of this group is greater than that of the whole sample.

Insert Tables IV-V about here

Table VI shows the classification of country of incorporation. 49 bonds of 24 firms belong to firms incorporated outside of the US. Each of these countries only has a small number of bonds and firms. Therefore, for the purpose of this study, they were all gathered in one group – *Incorporated out of US*. However, the distribution of the firms and bonds across countries does not seem to be representative of the population. Therefore, a dummy variable is included in the regression for incorporation outside the US merely for controlling purposes, but not for testing the inconsistency of ratings across countries.

Insert Tables VI about here

IV. Results

A. Estimation of hazard function

Table VII shows the results of three runs for estimation of the hazard function of companies with regard to S&P bond ratings on main-categories scale and one-digit industrial classification. In the first run, hazard function is estimated without using rating classifications. As expected, smaller *Size*, higher *Leverage*, lower *Profitability*, *Incorporation out of the US* and lower *Liquidity* increase companies' tendency to default. As expected *Liquidity*' s effect is insignificant. The significant negative coefficient of the dummy variable *Secured* indicates that provision of collateral indeed signals lower tendency to default. Analysis of industrial classification reveals that during the sample period some industries were significantly 'safer' than the others – Manufacturing, and Public Utilities.[16] Mining & Construction, and Wholesale & Retail were significantly riskier than other companies. Coefficients of cohort dummies show that issues from the 80's were subject to higher default risk compared with those issued in 90's.

[16] Note that the significance of the Industrial classification dummies depends on the composition of the benchmark (the omitted dummy variable for industrial classification) – in this case the services industry. Table III reveals that a larger fraction of this industry has experienced default compared to the whole population.

Insert Table VII about here

In the second run, hazard function is estimated using S&P ratings on main-categories scale and cohort dummies for year of issue. The results show that in general the higher the rating, the lower the default risk. Coefficients of rating classifications express two anomalies. First and as reflected in figure 1, they are not fully monotonic. The coefficient of AA is expected to be smaller than that of A, yet it appears to be larger.

Insert Figure 1 about here

Furthermore, the difference between most adjacent ratings is insignificant. Table VIII shows the t statistics for the differences between the rating coefficients as estimated in the second run. It appears that ratings AAA, AA and A are not significantly different from each other. However rating A is significantly different from rating BBB. It could be claimed that this is the result of the low number of default cases in each category. Yet, this should not have brought about the non-monotonic behavior of the point estimates. The results concerning the subcategorized ratings shown later support this non-monotonic and non-significant behavior of the ratings. However one interesting result is that ratings have at least some distinguishing power within each group of investment grades and speculative grades. Rating A is significantly better than rating BBB even though they are both investment grades, and rating BB is significantly better than B even though they are both speculative grades.

Insert Table VIII about here

The third run (table VII) shows the results of estimation of a hazard function considering rating information as well as firm-specific characteristics, industrial classification and cohort dummies. If rating is consistent across industries and countries, if it correctly incorporates all the specific characteristics of firms and if the rating categories are narrow enough, it should be expected that all the coefficients, except those of ratings dummies and *Secured*, are zero. Since a bond's rating is raised when it is secured, the coefficient of *Secured* is supposed to be positive.[17] Since the benchmark for rating dummies is the group of companies with rating lower than B, the coefficients of rating dummies are expected to be negative.

While the coefficient of none of the industrial classification dummies is significant by itself, the differences between some industries are significant. *Manufacturing* and *Public Utilities* industries were significantly less risky than firms from *Mining & Construction* and *Wholesale & Retail* with the same rating and firm characteristics.

The coefficients of the rating dummy variables are significant, as well as the difference between some coefficients. This is not general proof of the dominance of ratings over publicly available information in prediction of default, but it implies that the rating classification had a value added in prediction of default compared to the model based only on the other variables included in the estimation.

The coefficients of the dummy variables for the year of issue have the same signs as well as close values to the coefficients in the first run. If these dummy variables represent the macroeconomic situation at the date of rating, it can be concluded that ratings do not fully reflect the business cycles. This interpretation fits S&P rating methodology that ratings are assigned to reflect 'looking through the cycle'.

The results show that signs of coefficients of most firm specific variables are as in the first run. Coefficient of *Secured* is negative and significant – meaning that the rating does not fully incorporate the signaling of collateral provision. However the other firm-specific

[17] In the case of secured debt, rating is notched up. Therefore if two debts have equal ratings but one is secured and the other is not, the issuer of the secured debt has to have a lower rating compared to the other issuer. Therefore in such a case the coefficient of the dummy variable that indicates availability of collateral should be positive. Note that the signaling affect should already be included in the rating classification and therefore the third run's coefficients should be positive.

coefficients are insignificant. For instance, the coefficients of *Size* and *Profitability* are negative as in the first run but they are not significant. It should also be noted that it is possible that the coefficients of these specific variables were insignificant due to the broad definition of the industries and varying parameters. One criticism of ratings is that they cannot fully capture the varying affect of firm-specific variables across industries. For example, two firms with the same level of leverage but from two different industries might have different level of risk for two reasons. One source of the variation is the difference in the general risk of the two industries and the other is the different effect of leverage on risk in these two industries. Now consider a sample of firms from two different industries in the case that leverage is not correlated with industry. Once the industrial classification variable is omitted, the standard coefficient of the variable *Leverage* would be biased and larger than the true value (a typical result of omitted variables). Therefore, it might be that the coefficients of the firm specific variables were insignificant due to the fact that the industrial classifications were too broad.

Table IX reports the results in the case where industrial classification is tighter. In these regressions the industries *Mining & Construction* and *Wholesale & Retail* as well as *Services* (omitted dummy variable) are classified according to one digit SIC, while *Manufacturing* and *Public & Utilities* are sub-classified according to two-digit SIC. Now the third run, which includes all variables, shows that the coefficients of firm-specific variables become more significant and the coefficient of *Leverage* is already significant. This result suggests that the ratings are indeed not a sufficient statistic for some publicly available information. Furthermore, this disability might be a result of the fact that the rating did not fully capture the industry-based varying interpretation of these variables.

Insert Table IX about here

Table X shows the t statistics for the differences between pairs of industries. It appears that, after controlling for rating, some industries did indeed tend to default more than others. For example, while the coefficient of the industry *Mining & Construction* is insignificant comparing to the benchmark (the omitted industrial classification dummy variable) *Services*, it is significantly larger than *Manufacturing – Food & Tobacco* and others too. Table IX reveals that the coefficients of the industrial classification variables in the third run have the same sign as in the first run. This result can be interpreted as indicating that the ratings have not incorporated all this industrially oriented default risk.

Insert Table X about here

Narrowing the industrial classification to two-digit SIC, as shown in table XI, makes the coefficients of firms' specific variables in the third run even more significant. Now, not only *Secured* and *Leverage* are significant but *Size* also. These results support the thesis that ratings do not fully capture the varying affects of the firm specific variables across industries. The coefficients of most industrial classifications dummies are negative since the benchmark (group of 'other') happened to be riskier as indicated in table V.

Insert Table XI about here

B. Robustness

The results reveal that after conditioning for ratings, other publicly available information such as firms' specific variables and industrial classifications were still significant in explaining default probability. However there are several reasons to doubt whether this result indicates that S&P could have created better ratings.

B.1. Categorization

It could be said that even though some publicly available information was not fully incorporated in assigning the rating on main categories' scale, it has served to subcategorize the ratings classes. The first answer to this claim should be that many coefficients, especially those of industrial classifications, show that using these variables should have changed the ratings dramatically. For instance, the coefficient of *Food & Tobacco* industry in the third run of table XI is –2.856 while the difference between the coefficients of AAA and B according to that estimation is only 2.321. This means that any firm from this industry that was rated B, should have been rated AAA, at least ex-post.

However, the sub-categorized ratings can also be used to test the significance of the firms' characteristic variables. Table XII shows the results when the hazard function is estimated using sub-categorized ratings. The second run shows the case where rating dummy variables are used together with dummy variables for the year of issue. Once again it appears that the rating classifications are not fully monotonic (see figure 2).

Insert Figure 2 about here

It can be argued that this result might show that the sample does not represent the population. Figure 3 shows the log of average cumulative default rates in 15 years as reported by S&P.[18] This figure is based on a different sample and it includes all bonds and not only new bonds. This figure would be expected to monotonically increase which is not the case, especially when focusing on investment grade ratings. Hence, S&P statistical reports also support the thesis raised.

Insert Figure 3 about here

The second run in Table XII also reveals that the coefficients of many adjcant rating categories are not significantly different from each other. Table XIII shows the t statistics for the differences between coefficients of the rating dummy variables. There are no significant differences between subcategories within the same main category. For instance none of the coefficients for BB+, BB and BB- are significantly different from each other. Moreover, none of the ratings AAA, AA+, AA, AA-, A+, A, A- are significantly different from each other. The cumulative tests (part b of table XIII) reveals that in fact there is no significant difference between any of the 'investment grade' ratings. However, when looking at individual couples of ratings it can be seen that many of investment grade ratings were significantly different from rating BBB- or even BBB. However, when all these grades are put in one test, the null hypothesis cannot be rejected. Remember also that when main categorized ratings were used, the statistical test revealed that ratings AAA, AA, and A were significantly better than BBB. Therefore it appears that the sub-categorization of ratings makes the differences between the different sub-categories too noisy.

[18] See "Rating Performance 2000" by Standard & Poor's.

Insert Tables XII-XIII about here

The third run in table XII affirms the results from previous estimations; i.e. conditioning for rating information, publicly available information still has an explanatory power in predicting default. And the results are generally similar to those obtained when using main-categorized ratings. *Size* is now insignificant, but *Leverage* and *Secured* are still significant. As before all coefficients in the third run have the same sign as in the first run (except for the dummy variable for Food Stores). Therefore it can be concluded that the additional explanatory power of these variables is not eliminated even when sub-categorizing the rating classifications.

B.2. Issuers' ratings vs. Issues' ratings

It could be claimed that possibilities of improving the ratings are due to using bonds' ratings instead of issuers' ratings. However this point should not be so critical. Recall that not all bonds ratings are notched up or down. Furthermore, as indicated before, the difference between issuer's rating and issue's rating is up to 2 categories in the case of speculative-grade issuers and up to 1 sub-category in case of investment-grade issuers. Therefore, in many cases of notching (when issuer's rating is different from issue's rating), both ratings are still in the same main category. However, when using main-categories ratings, the results reveal that using the publicly available data would have changed the rating of many firms by more than one main category.

To address the question more thoroughly, the estimation is repeated using issuers' ratings instead of issues' rating. Table XIV shows the distribution of the sample across the different main-categories of rating classification and occurrence of default. The data on issuer's rating (or equivalently senior unsecured rating) could not be found for many observations. Hence, the number of observations decreased to 2487, of which 176 observations ended with default. Of the

144 observations that have been erased, 62 (about 43%) were observations that ended with default. Therefore the remaining database is biased toward more stable companies.

Insert Table XIV about here

Table XV shows the industrial classification of this sample. Comparison to table IV reveals that the fall in observation (compared to issues' ratings sample) is not homogenous across industries. For instance, the number of *Services* industry observations has decreased by 11.4% while the total sample has only decreased by 5.5%.

Insert Table XV about here

Table XVI shows the results of estimations when using the issuers' ratings. Most qualitative results remain. Almost all coefficients that were significant when using issues' ratings keep the same sign when using issuers' ratings. The dummy variables indicating *Mining & Construction* industry and issues of 1983, are the only variables whose signs in the new estimations differ from those achieved using the issues' ratings (table IX). When focusing on the third run, *Size* becomes significant (compared to table IX) and *Leverage* and *Secured* are still significant. These estimations reveal that the results are indeed robust to the type of rating used. Inconsistencies across industries still exist in the same pattern as found when using issues' ratings. To conclude, using the sub-sample of issuers' ratings creates some undesired statistical constrains but it also reveals that results achieved using the main sample are not biased due to using bonds' ratings instead of issuers' ratings.

Insert Table XVI about here

B.3. Ex-post shocks

The results show that ex-post, rating was not a sufficient statistic for some publicly available information existing at the time of rating. It could be suggested that the fact that these variables still have explanatory power in prediction of default, is due to some shocks that could not have been expected at the time of rating but have been correlated with these variables (such as *Size*, *Leverage*, *Secured* and industrial classifications). This question should be addressed in several directions. First, even if it is so, it could be asked what fraction of the total risk can be expected, and what fraction cannot. As shown before, considering the historical evidence, some industries should have a much different level of rating. Many firms that were graded speculative could get an investment grade. Therefore even if this critic is accepted, the results suggest that ratings can resemble only a part of the realized risk.

One way to test the vulnerability to ex-post shocks is to split the sample into two sub-samples and to check whether the 'anomalies' reported in the entire sample also exist in each sub-sample. The sample is split into two sub-samples. The first sub-sample includes issues during the years 1983-1988, and the other sub-sample includes issues during the years 1989-1993. To minimize the chances of exposure to the same shocks, the window for observation of cases of defaults must also be different. The only defaults accounted for in the first sub-sample are those during the years 1984-1989 and censorship was already taken into account in 1990. And the defaults accounted in the second sub-sample are those during the years 1990-2000. This method for constructing the sub-samples not only reduces the number of observations in each sub-sample but more importantly the cases of defaults. As can be seen in table XVII, the number of observations in the first sub-sample drops to 1453 of which 57 are cases of default and in the second sub-sample it drops to 1071 observations of which 52 are cases of default. These small sub-samples constrain the ability to repeat the same estimations as for the complete sample. Table XVIII shows that when using the one-digit SIC, the number of cases of default in each industry drops dramatically, and therefore there is no place for using two-digit SIC for industrial classification.

Insert Tables XVII-XVIII about here

Tables XIX and XX show the results of the three runs in each sub-sample. Since the number of observations and cases of default are low, a large number of significant coefficients are not to be expected. Recall that when the estimation includes one-digit industrial classification, some of the coefficients already become non-significant due to varying parameters within industries. Hence, the focus should be on the signs of the coefficients. The first runs for each sub-sample show that the sub-samples are quite representative and the estimated coefficients are as expected and even significant. The coefficients in the third runs for each sub-sample are almost as expected. In both sub-samples the coefficient of *Leverage* is positive and coefficients of *Quick Ratio* and *Profitability* are negative. However the coefficient of *Size* is positive, though very small, for the first sub-sample and negative in the second sub-sample. In general it can be concluded that these results show consistency across the two sub-samples. The slightly disturbing result for *Size* can be related to the small size of the sample.

Insert Tables XIX-XX about here

However, the coefficients of the industrial classifications are not so consistent across the two sub-samples. The order of the coefficients of the industrial classifications in the first sub-sample is first *Mining & Construction*, then *Manufacturing*, *Services*, *Wholesale & Retail* and the last *Public Utilities*. In the second sub-sample the order is first *Wholesale & Retail*, then *Mining&*

Construction, then *Services*, and *Manufacturing* and *Public Utilities* the last. The order is different.

To conclude, this exercise suggests that there is additional explanatory power in prediction of default when pointing to firm specific variables but not as much when pointing to industrial classifications. It seems that the rating agency was indeed not able to fully incorporate the varying meanings of the firm-specific variables across industries. However the ex-post inconsistency of ratings across industries might be still due to unexpected shocks.

V. Conclusion

In this paper quality of S&P ratings is tested ex-post. The results suggest that S&P categorization was not fully informative. Differences between most of adjcant categories and especially subcategories are not significant during the sample period and the sub-categorization is not even fully monotonic with respect to default risk. However it appears that the power of ratings is not just in differing between investment grade firms and speculative grade firms. Ratings can be used to some extent to differ between firms within each of these groups.

The study also shows that some publicly available information was not efficiently incorporated in the assignment of ratings. Combining data on collateral provision, leverage and even the size of the firms together with the rating, would improve the prediction of default comparing to using rating only. Once the sample is split into to two sub-samples and the estimation process repeated, these results appear to be quite robust along the sample period. The significance of this result also appears to depend on the broadness of industry definitions. Hence, it is possible to suggest that the lack of incorporation of this publicly available information in ratings is due to lack of integration of the varying interpretation of these variables across the different industries.

The industrial classification seems to significantly explain a portion of the default risk even after controlling for rating. This could lead to the suspicion that ratings also misincorporate industrial classification. However this result is not robust throughout the sample period and the thesis that it is due to some noise that has been correlated with industrial classification ex-post cannot be rejected.

In general, it appears that the ex-post default risk is greater than can be learned from ratings. However, it is hard to discern what portion of this risk could already have been expected at the time of rating. Nevertheless, if all anomalies shown in this study are due to noise, then it has to be asked what portion of the total default risk is systematic. It is also interesting to know what portion of this systematic risk is incorporated in ratings. For example, the finding that some industries were riskier than S&P projected at the time of assignment of rating might have been caused by an unexpected shock during the sample period. Suppose this is the case and the inconsistency across industries was due to unexpected shocks to industries, it is still possible to question the quality and relevance of ratings in the presence of such extreme unexpected shocks.

Using a unique database and employing a new-old statistical methodology, this study has been able to shed some light on the presence of these anomalies and offer some explanations. The paper has also shown some indications that these anomalies are systematic. However, the decomposition of the default risk into three components – systematic incorporated in rating, systematic not incorporated in rating and noise is beyond the capabilities of the database and the methodological approach adopted in this paper. Further research in this direction, together with exploration of the relevance to corporate bond pricing is desirable. It would also be interesting to test whether these anomalies only appear when the rating is assumed to target the prediction of default rather than prediction of default loss or credit quality transition.

References

Admati A.R. and P. Pfleiderer, (1986) “A Monopolistic Market for Information” *Journal of Economic Theory* 39: 400-438

Altman, E. I., (1968) "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *Journal of Finance*, September

Ammer, J. and F. Packer (2000), "How Consistent are Credit Ratings? A Geographical and Sectoral Analysis of Default Risk", *Board of Governors of the Federal Reserve System International Discussion Paper* No. 668

Bester, H. (1985), “Screening vs. Rationing in Credit Markets with Imperfect Information”, *The American Economic Review,* 75(4): 850-855

Blume, M. F. Lim and C. Mackinlay (1998), "The declining Credit Quality of U.S. Corporate Debt: Myth or Reality?”, *Journal of Finance*, August: 1389-1413

Cantor, R., T., Collins, E. Falkenstein, D. Hamilton, C.M. Hu, C.M. Chair, S. Nayar, R. Ray, E. Rutan and F. Zarin (2001), "Testing for Rating Consistency in Annual Default Rates", *Moody's Investor Service*

Cox, D. R. (1972), “Regression Models and Life Tables", *Journal of the Royal Statistical Society B,* 34: 187-220

Griffin, P. A. and A. Z. Sanvicente (1982), "Common Stock Returns and Ratings Changes: A Methodological Comparison", *Journal of Finance*, 37: 103-119

Guede, J. and T. Opler (1996), "The Determinants of the Maturity of Corporate Debt Issues", *Journal of Finance*, December: 1809-1833

Hand, J., R. Holthausen and R. Leftwich (1992), "The Effect of Bond Rating Agency Announcements and Bond and Stock Prices", *Journal of Finance*, June: 733-752

Holthausen, R. and R. Leftwich (1985), "The Effect of Bond Rating Changes on Common Stock Prices", *Journal of Financial Economics*, 17: 57-89

Horrigan J. O. (1966), "The Determination of Long-Term Credit Standing with Financial Ratios", *Journal of Accounting Research*, 4: 44-62

Jarrow, R. D. Lando and S. Turnbull (1997), "A Markov Model for the Term Structure of Credit Risk Spreads", *The Review of Financial Studies*, 10(2)

Kaplan, R. and G. Urwitz (1979), "Statistical Models of Bond ratings: A Methodological Inquiry", *Journal of Business*, April: 231-262

Kliger, D. and O. Sarig (2000), "The Information Value of Bond Ratings", *Journal of Finance*, December: 2879-2902

Liu, P., F.J. Seyyed and S.D. Smith (1999), "The Independent Impact of Credit Rating Changes - The Case of Moody's Rating Refinement on Yield Premiums", *Journal of Business Finance & Accounting*, 26(3)

Lizzeri, A. (1999), "Information Revelation and Certification Intermediaries", RAND Journal of Economics, vol. 30: 214-231

Partony, F. (1999), "The Siskel and Ebert of Financial Markets? Two Thumbs Down for the Credit Rating Agencies", *Washington University Law Quarterly* 77 (3)

Pinches, G. and J. Singleton (1978), "The Adjustment of Stock Prices to Bond Rating Changes", *Journal of Finance*, 33: 29-44

Pinches, G. E. and K. A. Mingo (1973), "A multivariate Analysis of Industrial Bond Ratings", *Journal of Finance*, 28: 1-18

Pogue, T. and R. Soldofsky (1969), "What's in a Bond Rating?", *Journal of Financial and Quantitative Analysis*, 4: 201-228

Standard & Poor's (2001), "Ratings Performance 2000"

Weinstein, M, "The effects of Rating Changes Announcement on Bond Prices", *Journal of Financial Economics*, December 1977: 329-350

West, R. R. (1970), "An Alternative Approach to Predicting Corporate Bond Rations", *Journal of Accounting Research*, 7: 118-127

West, R. R. (1973), "Bond Ratings, Bond Yields and Financial Regulation: Some Findings", *Journal of Law and Economics*, 16: 159-168

White, L. J, (2001), "The Credit Rating Industry: An Industrial Organization Analysis", *New York University, Center for Law and Business, Working Paper* # CLB-01-001

Appendix A

Historical Evidence on Term Structure of Hazard Rate

Table A-I-a shows the historical average cumulative default probabilities of the main rating categories up to fifteen years after issue as documented by S&P.[19] Use $F_r(T)$ to denote the average cumulative probability of default of rating r, T years after assigning the rating. Table A-I-b describes $f_r(T) = F_r(T) - F_r(T-1)$ - the average probability of default of rating r between time $T-1$ and time T and table A-I-c shows $\theta_r(T) = f_r(T) / [1 - F_r(T-1)]$ - the average hazard rate of default between time $T-1$ and time T. Figures A-1a to A-1i show $\theta_r(T)$ of each rating category up to 15 years after assigning the rating. These tables and figures suggest that the average hazard rate first increases over time and then decreases. The lower the rating, the faster the hazard rate reaches its maximum. However, it must be noted that such calculation is biased due to heterogeneity within each rating category. Such heterogeneity will induce the average hazard rate to be decreasing. The basic idea is quite simple. Suppose rating r includes two types of bonds that differ in their constant hazard rate to default. Use *High* to denote the bonds with the higher hazard rate and *Low* the firms with the lower hazard rate. As time passes, more firms of type *High* default than firms of type *Low*. Therefore the proportion of firms of type *Low* in group r increases over time. Calculating the average hazard rate of this rating category would show that the hazard rate decreases over time while in fact it is constant for each firm. If there is more heterogeneity among low-grade bonds, then their average hazard rate would decrease faster than that of high-grade bonds. Therefore, the differences in the historical time pattern of average hazard rate of S&P ratings may be the result of such heterogeneity within each rating category. Hence, the possibility that the time pattern of the hazard rate is unconditional on the firms' specific default risk, as assumed in this paper, cannot be ruled out.

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[19] See "Ratings Performance 2000", Standard and Poor's. These statistics are based on all bonds rated by S&P during the years 1981 to 2000.

Appendix B

Calculating the variable - T_{it}

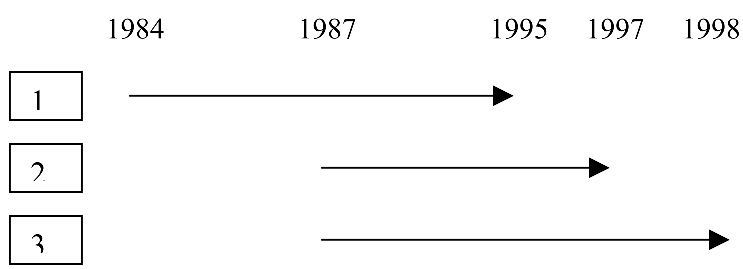
T_{it} is the time that the firm i has been exposed to default risk since the time t at which it issued a rated bond. T_{it} depends not only on the time to maturity of the bond issued at time t but on all of its bonds (including those issued before t and after t). Let $M_{it\xi}$ denote the year of maturity of bond ξ issued by firm i at time t.[20] Then,

$$T_{it} = \min\left(2000, T_{it}^{D}, \left(\max_{\substack{\iota \in (\text{all times the firm has issued new bond}),\\ \upsilon \in (\text{all bonds the firm has issued at each time } \upsilon)}} M_{\iota\tau\upsilon} \Big/ \left(\iota < \max\left(M_{i\varsigma\upsilon} / \varsigma < \tau\right)\right)\right)\right) - t$$

The following examples illustrate the formula.

Example 1

Suppose firm i issued bond 1 in 1984 with time of maturity 1995 and bonds 2 and 3 in 1987 with time of maturity 1997 and 1998 respectively. The firm has not defaulted. Then $M_{i\ 1984\ \ 1} = 1995$; $M_{i\ 1987\ \ 2} = 1997$ and $M_{i\ 1987\ \ 3} = 1998$.



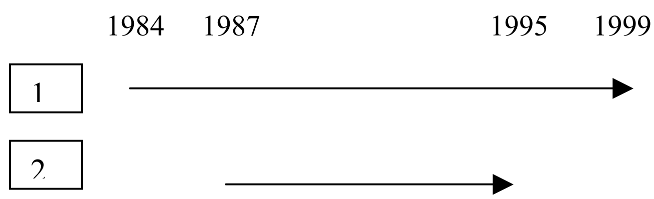
Then it can be said that from 1984, the firm was exposed to default risk till 1998, and therefore $T_{i\ 1984} = 14$. And from 1987, the firm was exposed to default risk till 1998, and therefore $T_{i\ 1987} = 11$.

Since it is still not known what the exact time of default will be ($T_{i\ 1984}^{D}$ and $T_{i\ 1987}^{D}$ are not known), both observations are censored and $s_{i\ 1984} = 0$ $s_{i\ 1987} = 0$.

[20] Some firms issue more than one type of bond in each year.

Example 2

Suppose firm i issued bond 1 in 1984 with time of maturity 1999 and bond 2 in 1987 with time of maturity 1995. The firm has not defaulted. Then $M_{i\ 1984\ \ 1} = 1999$; $M_{i\ 1987\ \ 2} = 1995$.

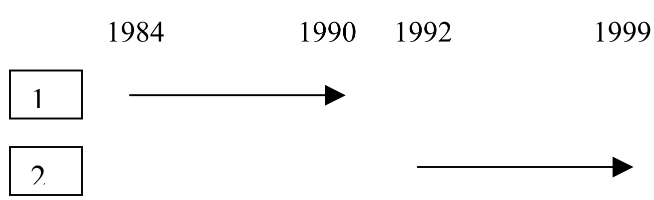


Then it can be said that from 1984, the firm was exposed to default risk till 1999, and therefore $T_{i\ 1984} = 15$. And from 1987, the firm was exposed to default risk till 1999 too, and therefore $T_{i\ 1987} = 12$.

Since it is still not known what the exact time of default will be ($T^D_{i\ 1984}$ and $T^D_{i\ 1987}$ are not known), both observations are censored and $s_{i\ 1984} = 0$ $s_{i\ 1987} = 0$.

Example 3

Suppose firm i issued bond 1 in 1984 with time of maturity 1990 and bond 2 in 1992 with time of maturity 1999. The firm has not defaulted. Then $M_{i\ 1984\ \ 1} = 1990$; $M_{i\ 1992\ \ 2} = 1999$.

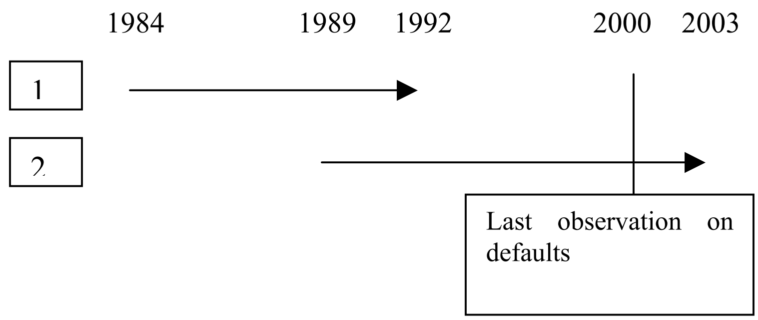


Then it can be said that from 1984, the firm was exposed to default risk till 1990 and there is no indication that the firm was exposed to default risk during 1991-1992. Hence $T_{i\ 1984} = 6$. And from 1992, the firm was exposed to default risk till 1999, and therefore $T_{i\ 1992} = 7$.

Since it is still not known what the exact time of default will be ($T^D_{i\ 1984}$ and $T^D_{i\ 1992}$ are not known), both observations are censored and $s_{i\ 1984} = 0$ $s_{i\ 1992} = 0$.

Example 4

Suppose firm i issued bond 1 in 1984 with time of maturity 1992 and bond 2 in 1989 with time of maturity 2003. The firm has not defaulted. Then $M_{i\ 1984\ 1} = 1992$; $M_{i\ 1989\ 2} = 2003$.

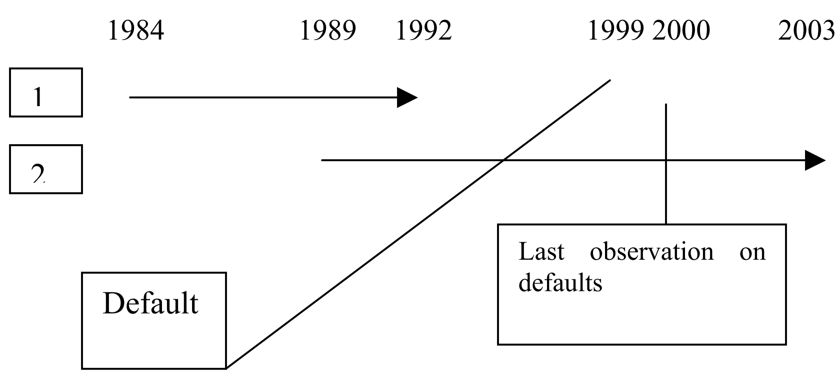


Then it can be said that from 1984, the firm was exposed to default risk till 2003 but this observation is censored from 2000 because the firm might default after 2000. Hence $T_{i\ 1984} = 16$. From 1989, the firm was exposed to default risk till 2003, unless default occurred in the years 2001-2003. Therefore the observation is censored after year 2000 and $T_{i\ 1989} = 11$.

Since it is still not known what the exact time of default will be ($T_{i\ 1984}^{D}$ and $T_{i\ 1992}^{D}$ are not known), both observations are censored and $s_{i\ 1984} = 0$ $s_{i\ 1989} = 0$.

Example 5

Suppose firm i issued bond 1 in 1984 with time of maturity 1992 and bond 2 in 1989 with time of maturity 2003. The firm defaulted in 1999. Then $M_{i\ 1984\ 1} = 1992$; $M_{i\ 1989\ 2} = 2003$.

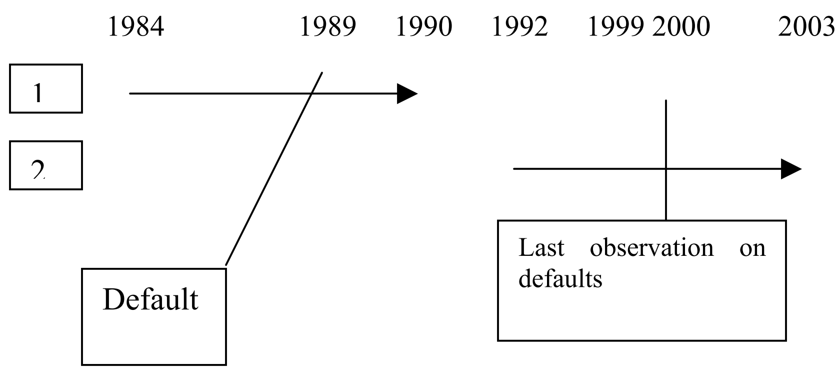


Then it can be said that from 1984 it took the firm $T_{i\ 1984} = 15$ to become default. From 1989 it took the firm $T_{i\ 1989} = 10$ years to become default.

Since default has occurred after both observations, then $s_{i\ 1984} = 1$ $s_{i\ 1989} = 1$.

Example 6

Suppose firm i issued bond 1 in 1984 with time of maturity 1990 and bond 2 in 1992 with time of maturity 2003. The firm defaulted in 1989. Then $M_{i\ 1984\ \ 1} = 1990$; $M_{i\ 1992\ \ 2} = 2003$.



Then it can be said that from 1984 it took the firm $T_{i\ 1984} = 5$ to default. From 1992, the firm was exposed to default risk till 2003, unless default occurred in the years 2001-2003. Therefore the observation is censored after year 2000 and $T_{i\ 1992} = 8$.

Since default occurred after the first observation and not after second observation, then $s_{i\ 1984} = 1$ and $s_{i\ 1992} = 0$.

Tables

Table I

Distribution of the Sample across S&P Main Ratings

The table describes the S&P rating classification of issues on the main rating scale and the occurrence of default since the issue of the rating throughout the period during which the issuer was observed in the sample.

	Bonds			***Issuers***		
Rating	***Not Default***	***Default***	***Total***	***Not Default***	***Default***	***Total***
AAA	*103*	*1*	*104*	*32*	*1*	*33*
AA	*408*	*9*	*417*	*108*	*4*	*112*
A	*708*	*11*	*719*	*175*	*6*	*181*
BBB	*516*	*24*	*540*	*152*	*14*	*166*
BB	*170*	*21*	*191*	*88*	*11*	*99*
B	*434*	*139*	*573*	*277*	*99*	*376*
CCC and Lower	*54*	*33*	*87*	*43*	*23*	*66*
Investment (AAA-BBB)	*1735*	*45*	*1780*	*467*	*25*	*492*
Speculative (BB and Lower)	*658*	*193*	*851*	*408*	*133*	*541*
Total	***2393***	***238***	***2631***	***875***	***158***	***1033***

Table II

Distribution of the Sample across S&P Subcategorized Ratings

The table describes the S&P rating classification of issues on the subcategorized rating scale and the occurrence of default since the issue of the rating throughout the period during which the firm was observed in the sample.

	Bonds			*Issuers*		
Sub-categorized Rating	***Not Default***	***Default***	***Total***	***Not Default***	***Default***	***Total***
AAA	*103*	*1*	*104*	*32*	*1*	*33*
AA+	*43*	*1*	*44*	*12*	*1*	*13*
AA	*206*	*6*	*212*	*56*	*2*	*58*
AA-	*159*	*2*	*161*	*40*	*1*	*41*
A+	*255*	*4*	*259*	*59*	*1*	*60*
A	*266*	*4*	*270*	*69*	*3*	*72*
A-	*187*	*3*	*190*	*47*	*2*	*49*
BBB+	*160*	*5*	*165*	*42*	*4*	*46*
BBB	*198*	*10*	*208*	*69*	*5*	*74*
BBB-	*158*	*9*	*167*	*41*	*5*	*46*
BB+	*56*	*8*	*64*	*23*	*2*	*25*
BB	*22*	*2*	*24*	*10*	*2*	*12*
BB-	*92*	*11*	*103*	*55*	*7*	*62*
B+	*120*	*27*	*147*	*71*	*21*	*92*
B	*130*	*39*	*169*	*74*	*26*	*100*
B-	*184*	*73*	*257*	*132*	*52*	*184*
CCC and Lower	*54*	*33*	*87*	*43*	*23*	*66*
Total	***2393***	***238***	***2631***	***875***	***158***	***1033***

Table III

One Digit Standardized Industrial Classification (SIC) of the Sample

The table describes the one digit standardized industrial classification of the issuers of all bonds in the sample and the occurrence of default since the issue of the new bond throughout the period during which the firm was observed in the sample.

	Bonds			***Issuers***		
1 Digit SIC	***Not Default***	***Default***	***Total***	***Not Default***	***Default***	***Total***
Mining & Construction	*85*	*21*	*106*	*41*	*15*	*56*
Manufacturing & Equipment	*1096*	*90*	*1186*	*435*	*65*	*500*
Public Utilities	*775*	*27*	*802*	*201*	*13*	*214*
Wholesale & Retail	*266*	*70*	*336*	*119*	*41*	*160*
Services	*171*	*30*	*201*	*79*	*24*	*103*
Total	**2393**	**238**	**2631**	**875**	**158**	**1033**

Table IV

1-2 Digit Standardized Industrial Classification (SIC) of the Sample

The table describes the 1-2 digit standardized industrial classification (SIC) of the issuers of all bonds in the sample and the occurrence of default since the issue of the new bond throughout the period during which the firm was observed in the sample. The industries Mining & Construction, Wholesale & Retail, and Services are classifies according to 1-digit SIC while industries Manufacturing, and Public Utilities are sub-classified according to the 2-digit SIC.

	Bonds			*Issuers*		
1 or 2 Digit Sic Classification	*Not Default*	*Default*	*Total*	*Not Default*	*Default*	*Total*
Mining & Construction	85	21	106	41	15	56
Manufacturing - Food & Tobacco	156	1	157	40	1	41
Manufacturing - Chemicals & Allied Products	173	5	178	68	3	71
Manufacturing - Indl, Comml Mchy, Computer Eq	93	11	104	48	9	57
Manufacturing - Elec, Oth Elec Eq, Ex Cmp	83	9	92	47	7	54
Manufacturing - Transportation Eq	106	7	113	37	7	44
Manufacturing - Others	485	57	542	195	38	233
Public Utilities - Communications	486	5	491	110	2	112
Public Utilities - Elec, Gas, Sanitary Serv.	122	15	137	36	7	43
Public Utilities - Others	167	7	174	55	4	59
Wholesale & Retail	266	70	336	119	41	160
Services	171	30	201	79	24	103
Total	***2393***	***238***	***2631***	***875***	***158***	***1033***

Table V

2 Digit Standardized Industrial Classification (SIC) of the Sample

Part a describes the 2 digit standardized industrial classification (SIC) of the issuers of all bonds in the sample and the occurrence of default since the issue of the new bond throughout the period during which the firm was observed in the sample. Each industrial classification consists of at least 15 firms and 19 observations (bonds). All other industries that have not reached these numbers are gathered in a group called 'other'. Part b describes the 2 digit standardized industrial classification (SIC) of the issuers in group 'other' and the occurrence of default since the issue of the new bond throughout the period during which the firm was observed in the sample.

Part a (Table V-a)

2 Digit SIC Classification	***Bonds***			***Issuers***		
	Not Default	***Default***	***Total***	***Not Default***	***Default***	***Total***
Oil & Gas Extraction	*55*	*13*	*68*	*21*	*9*	*30*
Construction (Bldg+Heavy+Others)	*14*	*5*	*19*	*11*	*4*	*15*
Food & Tobacco	*156*	*1*	*157*	*40*	*1*	*41*
Textile & Apparel	*25*	*9*	*34*	*16*	*8*	*24*
Paper & allied Products	*93*	*3*	*96*	*27*	*2*	*29*
Printing, Publishing & Allied	*50*	*1*	*51*	*19*	*1*	*20*
Chemicals & allied Products	*173*	*5*	*178*	*68*	*3*	*71*
Pete Refining and Related Inds	*90*	*6*	*96*	*21*	*1*	*22*
Rubber & Misc. Plastic Products	*21*	*4*	*25*	*16*	*3*	*19*
Primary Metal Industries	*41*	*6*	*47*	*21*	*6*	*27*
Fabr Metal, Ex Machy, Trans Eq.	*36*	*3*	*39*	*18*	*2*	*20*
Indl, Comml Mchy, Computer Eq	*93*	*11*	*104*	*48*	*9*	*57*
Elec, Oth Elec Eq, Ex Cmp	*83*	*9*	*92*	*47*	*7*	*54*
Transportation Eq	*106*	*7*	*113*	*37*	*7*	*44*
Measurement Instruments, Photo Goods, Watches	*64*	*3*	*67*	*25*	*3*	*28*
Misc. Manufacturing Industries	*22*	*2*	*24*	*11*	*2*	*13*
Transportation By Air	*54*	*8*	*62*	*16*	*3*	*19*
Communications	*167*	*7*	*174*	*55*	*4*	*59*
Elec, Gas, Sanitary Serv.	*486*	*5*	*491*	*110*	*2*	*112*
Durable Goods - Wholesale	*22*	*4*	*26*	*17*	*2*	*19*
Nondurable Goods - Wholesale	*49*	*1*	*50*	*19*	*1*	*20*
General Merchandise Stores	*56*	*20*	*76*	*11*	*12*	*23*
Food Stores	*43*	*19*	*62*	*23*	*9*	*32*
Eating and Drinking Places	*27*	*3*	*30*	*12*	*3*	*15*
Miscellaneous Retail	*30*	*10*	*40*	*20*	*7*	*27*
Business Services	*42*	*6*	*48*	*22*	*3*	*25*
Motion Pictures	*29*	*5*	*34*	*12*	*5*	*17*
Amusement and Recreation Svcs	*22*	*4*	*26*	*13*	*4*	*17*
Health services	*30*	*6*	*36*	*15*	*5*	*20*
*Other **	*214*	*52*	*266*	*84*	*30*	*114*
Total	***2393***	***238***	***2631***	***875***	***158***	***1033***

* For the composition of the group 'other' see table V-b.

Part b (Table V-b)

2 Digit SIC Classification	***Bonds***			***Firms***		
	Not Default	***Default***	***Total***	***Not Default***	***Default***	***Total***
Agriculture Production-Crops	*4*	*1*	*5*	*2*	*1*	*3*
Metal Mining	*9*	*2*	*11*	*5*	*1*	*6*
Mng, Quarry Nonmtl Minerals	*3*	*0*	*3*	*2*	*0*	*2*
Lumber and Wood Pds, Ex Furn	*22*	*7*	*29*	*6*	*3*	*9*
Furniture and Fixtures	*7*	*0*	*7*	*6*	*0*	*6*
Leather and Leather Products	*1*	*0*	*1*	*1*	*0*	*1*
Stone,Clay,Glass,Concrete Pd	*12*	*11*	*23*	*8*	*5*	*13*
Railroad Transportation	*52*	*0*	*52*	*10*	*0*	*10*
Transit and Passenger Trans	*0*	*3*	*3*	*0*	*1*	*1*
Motor Freight Trans,Warehous	*7*	*3*	*10*	*4*	*2*	*6*
Water Transportation	*6*	*1*	*7*	*4*	*1*	*5*
Transportation Services	*3*	*0*	*3*	*2*	*0*	*2*
Bldg Matl, Hardwr, Garden-Retl	*12*	*5*	*17*	*4*	*3*	*7*
Auto Dealers, Gas Stations	*5*	*0*	*5*	*2*	*0*	*2*
Apparel and Accessory Stores	*15*	*3*	*18*	*7*	*1*	*8*
Home Furniture and Equip Store	*7*	*5*	*12*	*4*	*3*	*7*
Real Estate	*1*	*1*	*2*	*0*	*1*	*1*
Holding,Other Invest Offices	*1*	*1*	*2*	*1*	*1*	*2*
Hotels, Other Lodging Places	*10*	*5*	*15*	*3*	*3*	*6*
Personal Services	*4*	*1*	*5*	*2*	*1*	*3*
Auto Repair, Services, Parking	*26*	*0*	*26*	*5*	*0*	*5*
Educational Services	*1*	*0*	*1*	*1*	*0*	*1*
Social Services	*0*	*1*	*1*	*0*	*1*	*1*
Engr,Acc,Resh,Mgmt,Rel Svcs	*6*	*1*	*7*	*5*	*1*	*6*
Nonclassifiable Establishmnt	*0*	*1*	*1*	*0*	*1*	*1*
Total	***214***	***52***	***266***	***84***	***30***	***114***

Table VI

Country of Incorporation of the Issuers in the Sample

The table describes the country of incorporation of the issuers of all bonds in the sample and the occurrence of default since the issue of the new bond throughout the period during which the firm was observed in the sample. Part a describes whether the issuer was incorporated in the US or outside the US and part b describes the country of incorporation for the firms incorporated outside the US.

Part a (Table VI-a)

Country of Incorporation	*Bonds*			*Issuers*		
	Not Default	*Default*	*Total*	*Not Default*	*Default*	*Total*
US	*2349*	*233*	*2582*	*855*	*154*	*1009*
Outside the US	*44*	*5*	*49*	*20*	*4*	*24*
Total	***2393***	***238***	***2631***	***875***	***158***	***1033***

Part b (Table VI-b)

Country of Incorporation	*Bonds*			*Issuers*		
	Not Default	*Default*	*Total*	*Not Default*	*Default*	*Total*
Australia	*1*	*1*	*2*	*1*	*1*	*2*
Bermuda	*2*	*1*	*3*	*2*	*1*	*3*
Canada	*3*	*1*	*4*	*3*	*1*	*4*
Cayman Islands	*3*	*0*	*3*	*1*	*0*	*1*
England	*16*	*0*	*16*	*5*	*0*	*5*
Japan	*8*	*0*	*8*	*4*	*0*	*4*
Netherlands	*7*	*2*	*9*	*2*	*1*	*3*
Panama	*4*	*0*	*4*	*2*	*0*	*2*
Total	***44***	***5***	***49***	***20***	***4***	***24***

Table VII

Estimation of Hazard Function when Using S&P Bonds' Ratings on Main-Categories scale and one-digit SIC

The sample includes 2631 bonds of 1033 non-financial companies issued from 1983 through 1993. 238 bonds (of 158 companies) defaulted in years 1983 through 2000. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P main categories rating of the issue at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). Industrial classification is based on one-digit SIC.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA	-	-	-3.787	(-3.67)	-3.370	(-3.20)
AA	-	-	-3.005	(-5.11)	-2.417	(-4.46)
A	-	-	-3.315	(-7.77)	-2.795	(-6.56)
BBB	-	-	-2.173	(-6.33)	-1.744	(-4.69)
BB	-	-	-1.343	(-4.09)	-1.144	(-3.42)
B	-	-	-0.521	(-2.51)	-0.485	(-2.30)
Firm's Characteristics:						
Size	-0.388	(-5.77)	-	-	-0.057	(-0.75)
Quick Ratio	0.010	(0.19)	-	-	-0.007	(-0.15)
Leverage	1.330	(3.77)	-	-	0.478	(1.31)
Profitability	-1.663	(-1.51)	-	-	-0.431	(-0.41)
Secured	-3.128	(-2.99)	-	-	-2.912	(-2.72)
Incorporated out of US	0.867	(1.79)	-	-	1.206	(2.47)
Industrial Classification:						
Mining & Construction	0.574	(1.63)	-	-	0.409	(1.18)
Manufacturing	-0.324	(-1.29)	-	-	-0.266	(-1.10)
Public Utilities	-0.475	(-1.24)	-	-	-0.333	(-0.88)
Wholesale & Retail	0.453	(1.70)	-	-	0.411	(1.58)

Table VII – *Continued*

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Cohorts:						
Issued in 1983	1.238	(2.81)	1.442	(3.33)	1.412	(3.20)
Issued in 1984	1.460	(3.25)	1.601	(3.73)	1.597	(3.57)
Issued in 1985	0.757	(1.70)	1.003	(2.32)	1.014	(2.29)
Issued in 1986	1.055	(2.62)	1.099	(2.73)	1.134	(2.80)
Issued in 1987	0.698	(1.65)	0.706	(1.69)	0.745	(1.77)
Issued in 1988	1.267	(3.05)	1.206	(2.89)	1.175	(2.81)
Issued in 1989	0.885	(1.92)	1.001	(2.27)	0.988	(2.22)
Issued in 1990	-0.261	(-0.39)	0.030	(0.04)	-0.034	(-0.05)
Issued in 1991	-0.910	(-1.18)	-0.735	(-0.95)	-0.690	(-0.91)
Issued in 1992	0.510	(1.23)	0.611	(1.48)	0.516	(1.24)

Table VIII

t Statistics for Differences between Rating Categories

The table shows the t statistics for the differences between the S&P main rating categories. The statistics are based on estimation of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. The variables in this estimation (second run in table VII) are dummy variables for S&P main rating categories classification and dummy variables for the year of issue.

Part a – t statistics for equal coefficients of couples of ratings

	AAA	**AA**	**A**	**BBB**	**BB**
AA	*0.45*				
A	*0.19*	*0.27*			
BBB	*2.36*	*1.68*	*6.15**		
BB	*5.42**	*6.67**	*18.93**	*5.19**	
B	*10.33**	*17.96**	*52.88**	*31.01**	*8.61**

* Significant at 5% level.

Part b – t statistics for equal coefficients of groups of ratings

AAA=AA	*0.45*
AAA=AA=A	*0.53*
AAA=AA=A=BBB	*7.53**
AAA=AA=A=BBB=BB	*22.32***
AAA=AA=A=BBB=BB=B	*90.57***

* Significant at 10% level.

** Significant at 5% level.

Table IX

Estimation of Hazard Function when Using S&P Bonds' Ratings on Main-Categories scale and one or two digit SIC

The sample includes 2631 bonds of 1033 non-financial companies issued from 1983 through 1993. 238 bonds (of 158 companies) defaulted in years 1983 through 2000. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P main categories rating of the issue at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). Industries *Mining & Construction* and *Wholesale & Retail* as well as the *Services* (omitted dummy variable) are classified according to one digit SIC, while *Manufacturing* and *Public & Utilities* are sub-classified according to two-digit SIC.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA	-	-	-3.787	(-3.67)	-2.934	(-2.89)
AA	-	-	-3.005	(-5.11)	-2.189	(-4.02)
A	-	-	-3.315	(-7.77)	-2.655	(-6.37)
BBB	-	-	-2.173	(-6.33)	-1.684	(-4.75)
BB	-	-	-1.343	(-4.09)	-1.159	(-3.51)
B	-	-	-0.521	(-2.51)	-0.508	(-2.49)
Firms' Characteristics:						
Size	-0.361	(-5.21)	-	-	-0.060	(-0.81)
Quick Ratio	0.037	(0.73)	-	-	0.015	(0.30)
Leverage	1.560	(4.24)	-	-	0.687	(1.78)
Profitability	-1.870	(-1.70)	-	-	-0.606	(-0.60)
Secured	-2.837	(-2.55)	-	-	-2.781	(-2.50)
Incorporated out of US	0.781	(1.60)	-	-	1.049	(2.09)
Industrial Classification:						
Mining & Construction	0.566	(1.61)	-	-	0.420	(1.22)
Manufacturing - Food & Tobacco	-2.468	(-2.39)	-	-	-2.238	(-2.17)
Manufacturing - Chemicals & Allied Products	-1.440	(-2.17)	-	-	-1.069	(-1.77)
Manufacturing - Indl, Comml Mchy, Computer Eq	-0.131	(-0.33)	-	-	-0.270	(-0.69)
Manufacturing - Elec, Oth Elec Eq, Ex Cmp	-0.249	(-0.54)	-	-	-0.274	(-0.60)
Manufacturing - Transportation Eq	-0.506	(-1.08)	-	-	-0.440	(-0.95)
Manufacturing - Others	-0.046	(-0.17)	-	-	-0.057	(-0.21)
Public Utilities - Communications	-0.945	(-1.60)	-	-	-0.923	(-1.53)
Public Utilities - Elec, Gas, Sanitary Serv.	-1.275	(-1.46)	-	-	-0.944	(-1.11)
Public Utilities - Others	0.392	(0.88)	-	-	0.458	(1.12)
Wholesale & Retail	0.445	(1.66)	-	-	0.402	(1.54)

Table IX – *Continued*

Variable	First Run Cofficient	First Run (t-statistic)	Second Run Cofficient	Second Run (t-statistic)	Third Run Cofficient	Third Run (t-statistic)
Cohorts:						
Issued in 1983	1.188	(2.70)	1.442	(3.33)	1.338	(3.02)
Issued in 1984	1.487	(3.33)	1.601	(3.73)	1.579	(3.56)
Issued in 1985	0.751	(1.69)	1.003	(2.32)	0.977	(2.21)
Issued in 1986	1.042	(2.59)	1.099	(2.73)	1.128	(2.80)
Issued in 1987	0.702	(1.67)	0.706	(1.69)	0.753	(1.81)
Issued in 1988	1.258	(3.07)	1.206	(2.89)	1.169	(2.81)
Issued in 1989	0.954	(2.14)	1.001	(2.27)	1.018	(2.29)
Issued in 1990	-0.249	(-0.38)	0.030	(0.04)	-0.048	(-0.07)
Issued in 1991	-0.902	(-1.17)	-0.735	(-0.95)	-0.663	(-0.87)
Issued in 1992	0.481	(1.17)	0.611	(1.48)	0.515	(1.24)

Table X

t Statistics for the Additional Industrial Default Risk after Conditioning for Ratings

The table shows the t statistics for the differences between the default risk of different industries after conditioning for the S&P main-categories rating. The statistics are based on estimation of a proportional hazard function of the form $\theta(T; x_{it}, t) = k(x_{it}, t) \cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it}, t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used for calculating the variance-covariance matrix and the standard errors of coefficients. The variables in this estimation (third run in table IX) are dummy variables for one-two digit standardized industrial classifications (SIC).

	Mining & Construction	Manufacturing - Food & Tobacco	Manufacturing - Chemicals & Allied Products	Manufacturing - Indl, Comml Mchy, Computer Eq	Manufacturing - Elec, Oth Elec Eq, Ex Cmp	Manufacturing - Transportation Eq	Manufacturing - Others	Public Utilities - Communications	Public Utilities - Elec, Gas, Sanitary Serv.
Manufacturing - Food & Tobacco	6.46**								
Manufacturing - Chemicals & Allied Products	5.51**	1.03							
Manufacturing - Indl, Comml Mchy, Computer Eq	2.47	3.43*	1.42						
Manufacturing - Elec, Oth Elec Eq, Ex Cmp	1.88	3.27*	1.27	0.00					
Manufacturing - Transportation Eq	2.96*	2.75*	0.81	0.10	0.08				
Manufacturing - Others	2.01	4.46**	2.78*	0.31	0.22	0.68			
Public Utilities - Communications	4.42**	1.33	0.03	0.96	0.84	0.47	2.00		
Public Utilities - Elec, Gas, Sanitary Serv.	2.42	1.00	0.02	0.55	0.51	0.29	1.07	0.00	
Public Utilities - Others	0.01	6.34**	5.14**	2.15	1.77	2.78*	1.56	4.17**	2.41
Wholesale & Retail	0.00	6.55**	5.97**	3.05*	2.13	3.48*	2.98*	4.93**	2.50

* Significant at 10% level. ** Significant at 5% level.

Table XI

Estimation of Hazard Function when Using S&P Bonds' Ratings on Main-Categories scale and two digit SIC

The sample includes 2631 bonds of 1033 non-financial companies issued from 1983 through 1993. 238 bonds (of 158 companies) defaulted in years 1983 through 2000. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t) = k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P main categories rating of the issue at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). The dummy variables of industrial classifications are according to 2-digit standardized industrial classification (SIC). All industries that included less than 15 observations were gathered in the group 'other'.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA	-	-	-3.787	(-3.67)	-2.822	(-2.59)
AA	-	-	-3.005	(-5.11)	-2.321	(-4.39)
A	-	-	-3.315	(-7.77)	-2.651	(-6.32)
BBB	-	-	-2.173	(-6.33)	-1.587	(-4.36)
BB	-	-	-1.343	(-4.09)	-1.177	(-3.69)
B	-	-	-0.521	(-2.51)	-0.501	(-2.44)
Firm's Characteristics:						
Size	-0.406	(-6.72)	-	-	-0.113	(-1.67)
Quick Ratio	0.018	(0.33)	-	-	0.007	(0.14)
Leverage	1.559	(4.24)	-	-	0.779	(2.07)
Profitability	-1.943	(-1.73)	-	-	-0.713	(-0.74)
Secured	-2.862	(-2.53)	-	-	-2.726	(-2.39)
Incorporated out of US	0.772	(1.57)	-	-	0.960	(1.89)

Table XI – *Continued*

Variable	First Run Coefficient	First Run (t-statistic)	Second Run Coefficient	Second Run (t-statistic)	Third Run Coefficient	Third Run (t-statistic)
Industrial Classification:						
Oil & Gas Extraction	0.206	(0.50)	-	-	-0.080	(-0.20)
Construction	-0.172	(-0.29)	-	-	-0.389	(-0.66)
Food & Tobacco	-2.946	(-2.87)	-	-	-2.856	(-2.80)
Textile & Apparel	0.144	(0.35)	-	-	-0.186	(-0.47)
Paper & allied Products	-1.385	(-1.81)	-	-	-1.361	(-1.79)
Printing, Publishing & Allied	-2.523	(-2.41)	-	-	-2.705	(-2.57)
Chemicals & allied Products	-1.970	(-2.88)	-	-	-1.765	(-2.84)
Pete Refining and Related Inds	-0.080	(-0.08)	-	-	-0.212	(-0.21)
Rubber & Misc. Plastic Products	-0.476	(-0.72)	-	-	-0.820	(-1.24)
Primary Metal Industries	-0.410	(-0.88)	-	-	-0.666	(-1.42)
Fabr Metal, Ex Machy, Trans Eq.	-1.164	(-1.49)	-	-	-1.122	(-1.46)
Indl, Comml Mchy, Computer Eq	-0.666	(-1.69)	-	-	-0.960	(-2.48)
Elec, Oth Elec Eq, Ex Cmp	-0.795	(-1.73)	-	-	-0.959	(-2.10)
Transportation Eq	-1.022	(-2.15)	-	-	-1.115	(-2.38)
Measurement Instruments, Photo Goods, Watches	-1.704	(-2.72)	-	-	-1.781	(-2.82)
Misc. Manufacturing Industries	-1.210	(-1.56)	-	-	-1.608	(-2.15)
Transportation By Air	-0.301	(-0.52)	-	-	-0.536	(-1.08)
Communications	-1.445	(-2.43)	-	-	-1.576	(-2.61)
Elec, Gas, Sanitary Serv.	-1.769	(-2.03)	-	-	-1.590	(-1.86)
Durable Goods - Wholesale	-1.200	(-1.86)	-	-	-1.252	(-1.90)
Nondurable Goods - Wholesale	-2.348	(-2.23)	-	-	-2.294	(-2.16)
General Merchandise Stores	0.791	(1.84)	-	-	0.745	(1.98)
Food Stores	0.256	(0.71)	-	-	-0.128	(-0.36)
Eating and Drinking Places	-1.085	(-1.57)	-	-	-1.168	(-1.77)
Miscellaneous Retail	-0.026	(-0.06)	-	-	-0.393	(-0.79)
Business Services	-0.654	(-1.33)	-	-	-0.866	(-1.78)
Motion Pictures	-0.540	(-1.04)	-	-	-0.855	(-1.64)
Amusement and Recreation Svcs	-0.616	(-1.13)	-	-	-1.004	(-1.78)
Health services	-0.404	(-0.82)	-	-	-0.763	(-1.59)
Cohorts:						
Issued in 1983	1.316	(3.10)	1.442	(3.33)	1.441	(3.32)
Issued in 1984	1.501	(3.41)	1.601	(3.73)	1.523	(3.38)
Issued in 1985	0.870	(1.98)	1.003	(2.32)	1.076	(2.44)
Issued in 1986	1.068	(2.67)	1.099	(2.73)	1.119	(2.76)
Issued in 1987	0.726	(1.73)	0.706	(1.69)	0.770	(1.81)
Issued in 1988	1.218	(2.91)	1.206	(2.89)	1.117	(2.63)
Issued in 1989	1.036	(2.34)	1.001	(2.27)	1.088	(2.42)
Issued in 1990	-0.249	(-0.38)	0.030	(0.04)	-0.085	(-0.13)
Issued in 1991	-0.838	(-1.10)	-0.735	(-0.95)	-0.608	(-0.81)
Issued in 1992	0.460	(1.11)	0.611	(1.48)	0.496	(1.18)

Table XII

Estimation of Hazard Function when Using Sub-Categories of S&P Bonds' Ratings and two digit SIC

The sample includes 2631 bonds of 1033 non-financial companies issued from 1983 through 1993. 238 bonds (of 158 companies) defaulted in years 1983 through 2000. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P rating of the issue at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). The dummy variables of industrial classifications are according to 2-digit standardized industrial classification (SIC). All industries that included less than 15 observations were gathered in the group 'other'.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA	-	-	-3.794	(-3.67)	-2.902	(-2.66)
AA+	-	-	-3.109	(-3.01)	-1.951	(-2.39)
AA	-	-	-2.791	(-4.78)	-2.323	(-3.82)
AA-	-	-	-3.448	(-4.72)	-2.719	(-4.31)
A+	-	-	-3.265	(-4.46)	-2.650	(-3.61)
A	-	-	-3.375	(-5.18)	-2.876	(-4.44)
A-	-	-	-3.326	(-5.47)	-2.538	(-4.13)
BBB+	-	-	-2.670	(-5.40)	-2.041	(-3.91)
BBB	-	-	-2.049	(-3.76)	-1.500	(-2.79)
BBB-	-	-	-1.949	(-5.17)	-1.499	(-3.65)
BB+	-	-	-1.281	(-2.60)	-1.015	(-2.14)
BB	-	-	-1.436	(-1.91)	-1.187	(-1.52)
BB-	-	-	-1.388	(-3.75)	-1.326	(-3.71)
B+	-	-	-0.769	(-2.81)	-0.802	(-2.99)
B	-	-	-0.558	(-2.11)	-0.465	(-1.81)
B-	-	-	-0.405	(-1.85)	-0.419	(-1.86)
Firm's Characteristics:						
Size	-0.406	(-6.72)	-	-	-0.096	(-1.42)
Quick Ratio	0.018	(0.33)	-	-	0.003	(0.05)
Leverage	1.559	(4.24)	-	-	0.721	(1.91)
Profitability	-1.943	(-1.73)	-	-	-0.811	(-0.82)
Secured	-2.862	(-2.53)	-	-	-2.697	(-2.35)
Incorporated out of US	0.772	(1.57)	-	-	0.960	(1.89)

Table XII – *Continued*

Variable	First Run Coefficient	First Run (t-statistic)	Second Run Coefficient	Second Run (t-statistic)	Third Run Coefficient	Third Run (t-statistic)
Industrial Classification:						
Oil & Gas Extraction	0.206	(0.50)	-	-	-0.103	(-0.25)
Construction	-0.172	(-0.29)	-	-	-0.364	(-0.60)
Food & Tobacco	-2.946	(-2.87)	-	-	-2.860	(-2.81)
Textile & Apparel	0.144	(0.35)	-	-	-0.229	(-0.58)
Paper & allied Products	-1.385	(-1.81)	-	-	-1.369	(-1.81)
Printing, Publishing & Allied	-2.523	(-2.41)	-	-	-2.751	(-2.61)
Chemicals & allied Products	-1.970	(-2.88)	-	-	-1.747	(-2.86)
Pete Refining and Related Inds	-0.080	(-0.08)	-	-	-0.239	(-0.23)
Rubber & Misc. Plastic Products	-0.476	(-0.72)	-	-	-0.860	(-1.29)
Primary Metal Industries	-0.410	(-0.88)	-	-	-0.629	(-1.34)
Fabr Metal, Ex Machy, Trans Eq.	-1.164	(-1.49)	-	-	-1.139	(-1.50)
Indl, Comml Mchy, Computer Eq	-0.666	(-1.69)	-	-	-0.952	(-2.43)
Elec, Oth Elec Eq, Ex Cmp	-0.795	(-1.73)	-	-	-0.983	(-2.16)
Transportation Eq	-1.022	(-2.15)	-	-	-1.117	(-2.36)
Measurement Instruments, Photo Goods, Watches	-1.704	(-2.72)	-	-	-1.818	(-2.88)
Misc. Manufacturing Industries	-1.210	(-1.56)	-	-	-1.642	(-2.21)
Transportation By Air	-0.301	(-0.52)	-	-	-0.597	(-1.16)
Communications	-1.445	(-2.43)	-	-	-1.612	(-2.65)
Elec, Gas, Sanitary Serv.	-1.769	(-2.03)	-	-	-1.610	(-1.93)
Durable Goods - Wholesale	-1.200	(-1.86)	-	-	-1.311	(-1.98)
Nondurable Goods - Wholesale	-2.348	(-2.23)	-	-	-2.335	(-2.20)
General Merchandise Stores	0.791	(1.84)	-	-	0.749	(1.94)
Food Stores	0.256	(0.71)	-	-	-0.152	(-0.42)
Eating and Drinking Places	-1.085	(-1.57)	-	-	-1.150	(-1.76)
Miscellaneous Retail	-0.026	(-0.06)	-	-	-0.360	(-0.73)
Business Services	-0.654	(-1.33)	-	-	-0.826	(-1.73)
Motion Pictures	-0.540	(-1.04)	-	-	-0.830	(-1.57)
Amusement and Recreation Svcs	-0.616	(-1.13)	-	-	-0.989	(-1.76)
Health services	-0.404	(-0.82)	-	-	-0.786	(-1.63)
Cohorts:						
Issued in 1983	1.316	(3.10)	1.441	(3.31)	1.466	(3.33)
Issued in 1984	1.501	(3.41)	1.572	(3.64)	1.483	(3.25)
Issued in 1985	0.870	(1.98)	0.974	(2.25)	1.075	(2.45)
Issued in 1986	1.068	(2.67)	1.058	(2.63)	1.080	(2.66)
Issued in 1987	0.726	(1.73)	0.664	(1.59)	0.738	(1.74)
Issued in 1988	1.218	(2.91)	1.170	(2.78)	1.096	(2.56)
Issued in 1989	1.036	(2.34)	0.981	(2.21)	1.058	(2.34)
Issued in 1990	-0.249	(-0.38)	-0.008	(-0.01)	-0.137	(-0.21)
Issued in 1991	-0.838	(-1.10)	-0.731	(-0.94)	-0.627	(-0.84)
Issued in 1992	0.460	(1.11)	0.611	(1.47)	0.504	(1.20)

Table XIII

t Statistics for Differences between Rating Categories

The table shows the t statistics for the differences between the S&P rating sub-categories. The statistics are based on estimation of a proportional hazard function of the form $\theta(T; x_{it}, t) = k(x_{it}, t) \cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it}, t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. The variables in this estimation (second run in table VII) are dummy variables for S&P main rating categories classification and dummy variables for the year of issue.

Part a – t statistics for equal coefficients of couples of ratings

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B
AA+	0.23														
AA	0.75	0.10													
AA-	0.08	0.20	2.24												
A+	0.18	0.04	0.34	0.07											
A	0.13	0.05	0.48	0.01	0.01										
A-	0.16	0.03	0.43	0.02	0.00	0.00									
BBB+	1.03	0.15	0.03	0.83	0.50	0.85	0.81								
BBB	2.40	0.87	0.95	2.53	1.98	2.79*	2.82*	1.02							
BBB-	2.99*	1.18	1.61	3.59*	2.86*	4.62**	4.30**	1.66	0.03						
BB+	5.12**	2.65	4.20**	6.36**	5.53**	8.28**	7.65**	6.08**	1.30	1.83					
BB	3.56*	1.75	2.10	3.79*	3.21*	4.06**	4.08**	2.01	0.48	0.40	0.03				
BB-	5.12**	2.58	4.49**	6.74**	5.82**	8.77**	8.56**	5.29**	1.24	1.58	0.04	0.00			
B+	8.62**	5.06**	11.00**	12.72**	11.55**	16.40**	17.64**	15.81**	5.73**	9.41**	1.12	0.76	3.10*		
B	9.92**	6.30**	13.84**	15.58**	14.27**	20.23**	20.74**	18.32**	7.83**	13.61**	2.15	1.33	5.80**	0.62	
B-	11.02**	6.88**	16.08**	16.91**	15.68**	22.49**	24.25**	22.78**	9.97**	18.93**	3.42*	1.90	8.11**	2.46	0.50

* Significant at 5% level. ** Significant at 10% level.

Part b – t statistics for equal coefficients of groups of ratings

AAA = AA+	*0.23*
AAA = AA+ = AA	*0.78*
AAA = AA+ = AA = AA-	*5.01*
AAA = AA+ = AA = AA- = A+	*5.17*
AAA = AA+ = AA = AA- = A+ = A	*5.67*
AAA = AA+ = AA = AA- = A+ = A = A-	*5.85*
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+	*6.47*
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB	*9.09*
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB-	*14.22*
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB- = BB+	*21.14***
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB- = BB+ = BB	*22.65***
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB- = BB+ = BB = BB-	*28.37***
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB- = BB+ = BB = BB- = B+	*59.4***
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB- = BB+ = BB = BB- = B+ = B	*86.78***
AAA = AA+ = AA = AA- = A+ = A = A- = BBB+ = BBB = BBB- = BB+ = BB = BB- = B+ = B = B-	*107.26***

* Significant at 5% level. ** Significant at 10% level.

Table XIV

Distribution of the Sample across S&P Main Issuers' Ratings

The table describes the S&P issuers' rating classification of issues on the main rating scale and the occurrence of default since the issue of the rating through the period the issuer was observed in the sample.

	Bonds			Firms		
Rating	**Not Default**	**Default**	**Total**	**Not Default**	**Default**	**Total**
AAA	*106*	*1*	*107*	*23*	*1*	*24*
AA	*398*	*7*	*405*	*87*	*4*	*91*
A	*699*	*15*	*714*	*171*	*8*	*179*
BBB	*556*	*24*	*580*	*162*	*9*	*171*
BB	*302*	*32*	*334*	*153*	*19*	*172*
B	*242*	*92*	*334*	*156*	*61*	*217*
CCC and Lower	*8*	*5*	*13*	*3*	*4*	*7*
Total	***2311***	***176***	***2487***	***755***	***106***	***861***

Table XV

1-2 Digit Standardized Industrial Classification (SIC) of the Sample when using Issuers' Ratings

The table describes the 1-2 digit standardized industrial classification (SIC) of the issuers of all bonds in the sample (when using issuers' ratings) and the occurrence of default since the issue of the new bond through the period the firm was observed in the sample. The industries Mining & Construction, Wholesale & Retail, and Services are classifies according to 1-digit SIC while industries Manufacturing, and Public Utilities are sub-classified according to the 2-digit SIC.

	Bonds			Firms		
1 or 2 Digit Sic Classification	*Not Default*	*Default*	*Total*	*Not Default*	*Default*	*Total*
Mining & Construction	*87*	*7*	*94*	*41*	*4*	*45*
Manufacturing - Food & Tobacco	*169*	*1*	*170*	*36*	*1*	*37*
Manufacturing - Chemicals & Allied Products	*183*	*5*	*188*	*66*	*2*	*68*
Manufacturing - Indl, Comml Mchy, Computer Eq	*90*	*6*	*96*	*44*	*4*	*48*
Manufacturing - Elec, Oth Elec Eq, Ex Cmp	*84*	*7*	*91*	*43*	*4*	*47*
Manufacturing - Transportation Eq	*102*	*5*	*107*	*31*	*5*	*36*
Manufacturing - Others	*489*	*45*	*534*	*173*	*27*	*200*
Public Utilities - Communications	*430*	*5*	*435*	*85*	*2*	*87*
Public Utilities - Elec, Gas, Sanitary Serv.	*120*	*12*	*132*	*32*	*6*	*38*
Public Utilities - Others	*158*	*6*	*164*	*47*	*4*	*51*
Wholesale & Retail	*243*	*55*	*298*	*90*	*30*	*120*
Services	*156*	*22*	*178*	*67*	*17*	*84*
Total	***2311***	***176***	***2487***	***755***	***106***	***861***

Table XVI

Estimation of Hazard Function when Using S&P Issuers' Ratings on Main-Categories scale and one or two digit SIC

The sample includes 2487 bonds of 861 non-financial companies issued from 1983 through 1993. 176 bonds (of 106 companies) defaulted in years 1983 through 2000. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P issuer's main categories rating at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). Industries *Mining & Construction* and *Wholesale & Retail* as well as the *Services* (omitted dummy variable) are classified according to one digit SIC, while *Manufacturing* and *Public & Utilities* are sub-classified according to two-digit SIC.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA	-	-	-3.215	(-3.73)	-1.921	(-2.05)
AA	-	-	-3.338	(-5.15)	-2.296	(-3.50)
A	-	-	-3.123	(-5.35)	-2.315	(-4.87)
BBB	-	-	-2.404	(-4.65)	-1.790	(-4.01)
BB	-	-	-1.603	(-3.35)	-1.496	(-3.59)
B	-	-	-0.547	(-1.26)	-0.695	(-1.84)
Firm's Characteristics:						
Size	-0.395	(-4.89)	-	-	-0.213	(-2.02)
Quick Ratio	-0.012	(-0.17)	-	-	-0.026	(-0.42)
Leverage	1.595	(3.89)	-	-	1.049	(2.47)
Profitability	-1.803	(-1.39)	-	-	-0.923	(-0.76)
Secured	-2.444	(-2.21)	-	-	-2.393	(-2.21)
Incorporated out of US	0.325	(0.52)	-	-	0.336	(0.52)
Industrial Classification:						
Mining & Construction	-0.417	(-0.81)	-	-	-0.390	(-0.78)
Manufacturing - Food & Tobacco	-2.525	(-2.44)	-	-	-2.423	(-2.36)
Manufacturing - Chemicals & Allied Products	-1.408	(-1.73)	-	-	-1.089	(-1.50)
Manufacturing - Indl, Comml Mchy, Computer Eq	-0.639	(-1.15)	-	-	-0.705	(-1.25)
Manufacturing - Elec, Oth Elec Eq, Ex Cmp	-0.400	(-0.80)	-	-	-0.458	(-0.92)
Manufacturing - Transportation Eq	-0.668	(-1.21)	-	-	-0.626	(-1.11)
Manufacturing - Others	-0.183	(-0.56)	-	-	-0.108	(-0.33)
Public Utilities - Communications	-1.001	(-1.61)	-	-	-0.823	(-1.37)
Public Utilities - Elec, Gas, Sanitary Serv.	-1.247	(-1.42)	-	-	-1.002	(-1.18)
Public Utilities - Others	0.311	(0.68)	-	-	0.242	(0.57)
Wholesale & Retail	0.426	(1.41)	-	-	0.432	(1.48)

Table XVI – *Continued*

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Cohorts:						
Issued in 1983	-0.632	(-0.83)	-0.118	(-0.16)	-0.328	(-0.43)
Issued in 1984	0.783	(1.37)	0.847	(1.60)	0.840	(1.52)
Issued in 1985	0.298	(0.62)	0.508	(1.13)	0.431	(0.91)
Issued in 1986	0.545	(1.37)	0.602	(1.53)	0.580	(1.45)
Issued in 1987	0.350	(0.84)	0.328	(0.82)	0.277	(0.66)
Issued in 1988	0.873	(2.20)	0.813	(1.99)	0.819	(2.06)
Issued in 1989	0.482	(1.07)	0.523	(1.20)	0.516	(1.18)
Issued in 1990	-0.856	(-1.12)	-0.856	(-1.11)	-0.782	(-1.03)
Issued in 1991	-0.789	(-1.04)	-0.786	(-1.00)	-0.699	(-0.94)
Issued in 1992	0.364	(0.95)	0.438	(1.14)	0.370	(0.97)

Table XVII

Distribution of the Sub-samples across S&P Main Rating Categories

The table describes the S&P rating classification of issues on the main rating scale and the occurrence of default since the issue of the rating through the period the issuer was observed in the sub-sample.

Part a – first sub-sample – issues during the years 1983-1988 and defaults during the years 1984-1989

	Bonds			Firms		
Rating	*Not Default*	*Default*	*Total*	*Not Default*	*Default*	*Total*
AAA	*54*	*0*	*54*	*23*	*0*	*23*
AA	*236*	*3*	*239*	*94*	*1*	*95*
A	*374*	*3*	*377*	*145*	*1*	*146*
BBB	*249*	*4*	*253*	*120*	*3*	*123*
BB	*103*	*3*	*106*	*65*	*3*	*68*
B	*321*	*32*	*353*	*237*	*28*	*265*
CCC and Lower	*59*	*12*	*71*	*46*	*11*	*57*
Total	***1396***	***57***	***1453***	***730***	***47***	***777***

Part b – second sub-sample – issues during the years 1989-1993 and defaults during the years 1990-2000

	Bonds			Firms		
Rating	*Not Default*	*Default*	*Total*	*Not Default*	*Default*	*Total*
AAA	*41*	*0*	*41*	*24*	*0*	*24*
AA	*159*	*0*	*159*	*60*	*0*	*60*
A	*299*	*2*	*301*	*134*	*2*	*136*
BBB	*255*	*5*	*260*	*129*	*4*	*133*
BB	*76*	*6*	*82*	*55*	*6*	*61*
B	*177*	*37*	*214*	*145*	*34*	*179*
CCC and Lower	*12*	*2*	*14*	*11*	*2*	*13*
Total	***1019***	***52***	***1071***	***558***	***48***	***606***

Table XVIII

One Digit Standardized Industrial Classification (SIC) of the Sub-samples

The table describes the 1 digit standardized industrial classification (SIC) of the issuers of all bonds in the sub-sample and the occurrence of default since the issue of the new bond through the period the firm was observed in the sub-sample.

Part a – first sub-sample – issues during the years 1983-1988 and defaults during the years 1984-1989

	Bonds			Firms		
Industry	*Not Default*	*Default*	*Total*	*Not Default*	*Default*	*Total*
Mining & Construction	*42*	*12*	*54*	*27*	*11*	*38*
Manufacturing & Equipment	*673*	*30*	*703*	*365*	*23*	*388*
Public Utilities	*378*	*5*	*383*	*160*	*3*	*163*
Wholesale & Retail	*188*	*5*	*193*	*112*	*5*	*117*
Services	*115*	*5*	*120*	*66*	*5*	*71*
Total	***1396***	***57***	***1453***	***730***	***47***	***777***

Part b – second sub-sample – issues during the years 1989-1993 and defaults during the years 1990-2000

	Bonds			Firms		
Industry	*Not Default*	*Default*	*Total*	*Not Default*	*Default*	*Total*
Mining & Construction	*45*	*6*	*51*	*28*	*4*	*32*
Manufacturing & Equipment	*426*	*15*	*441*	*245*	*14*	*259*
Public Utilities	*363*	*6*	*369*	*154*	*6*	*160*
Wholesale & Retail	*116*	*19*	*135*	*77*	*18*	*95*
Services	*69*	*6*	*75*	*54*	*6*	*60*
Total	***1019***	***52***	***1071***	***558***	***48***	***606***

Table XIX

Estimation of Hazard Function when Using S&P Issues' Ratings on Main-Categories scale and one-digit SIC for the First Sub-sample

The sample includes 1453 bonds of 777 non-financial companies issued from 1983 through 1988. 57 bonds (of 47 companies) defaulted during the years 1984 through 1989. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P main categories rating of the issue at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). Industrial classification is based on one-digit SIC.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA or AA	-	-	-3.405	(-3.30)	-3.299	(-5.56)
A	-	-	-3.627	(-4.50)	-3.531	(-6.50)
BBB	-	-	-3.029	(-4.48)	-3.033	(-4.08)
BB	-	-	-2.501	(-3.93)	-2.514	(-4.07)
B	-	-	-1.187	(-3.36)	-1.361	(-4.01)
Firm's Characteristics:						
Size	-0.372	(-1.82)	-	-	0.018	(0.09)
Quick Ratio	-0.048	(-0.37)	-	-	-0.068	(-0.53)
Leverage	2.341	(2.49)	-	-	0.840	(0.88)
Profitability	-4.008	(-1.74)	-	-	-2.336	(-1.11)
Industrial Classification:						
Mining & Construction	1.378	(2.55)	-	-	1.303	(2.49)
Manufacturing	0.471	(0.93)	-	-	0.460	(0.95)
Public Utilities	-0.820	(-1.06)	-	-	-0.602	(-0.80)
Wholesale & Retail	-0.376	(-0.57)	-	-	-0.425	(-0.66)
Cohorts:						
Issued in 1983	-0.138	(-0.16)	0.371	(0.45)	0.398	(0.46)
Issued in 1984	-0.147	(-0.17)	0.007	(0.01)	0.168	(0.19)
Issued in 1985	-0.877	(-0.94)	-0.685	(-0.79)	-0.373	(-0.40)
Issued in 1986	-1.017	(-1.16)	-0.901	(-1.04)	-0.790	(-0.90)
Issued in 1987	-1.142	(-1.33)	-1.101	(-1.28)	-0.895	(-1.03)

Table XX

Estimation of Hazard Function when Using S&P Issues' Ratings on Main-Categories scale and one-digit SIC for the Second Sub-sample

The sample includes 1071 bonds of 606 non-financial companies issued from 1989 through 1993. 52 bonds (of 48 companies) defaulted during the years 1990 through 2000. The table describes the results of estimations of a proportional hazard function of the form $\theta(T;x_{it},t) = k(x_{it},t) \cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the time pattern $k_2(T)$. Clustering is used to calculate the variance-covariance matrix and the standard errors of coefficients. Dummy variables AAA to B indicate S&P main categories rating of the issue at the date of issue. *Size* is ln(*Total Assets*). *Quick ratio* is the difference between *Current Assets* and *Inventories* divided by *Current Liabilities* and is a proxy for liquidity. *Leverage* is *Total Liabilities* divided by *Total Assets*. *Profitability* is *EBIT* divided by *Total Assets*. *Secured* is a dummy variable indicating whether the company provided collateral for the issue (such as First Mortgage, Equipment Trust or other). Industrial classification is based on one-digit SIC.

Variable	First Run		Second Run		Third Run	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Rating:						
AAA or AA or A	-	-	-3.329	(-3.27)	-2.580	(-1.87)
BBB	-	-	-1.754	(-2.08)	-1.343	(-1.16)
BB	-	-	-0.340	(-0.40)	-0.256	(-0.24)
B	-	-	0.319	(0.43)	0.257	(0.27)
Firm's Characteristics:						
Size	-0.537	(-6.44)	-	-	-0.221	(-2.02)
Quick Ratio	-0.041	(-0.54)	-	-	-0.036	(-0.36)
Leverage	0.870	(2.00)	-	-	0.117	(0.24)
Profitability	-2.696	(-1.67)	-	-	-1.680	(-1.01)
Industrial Classification:						
Mining & Construction	0.797	(1.25)	-	-	0.730	(1.19)
Manufacturing	-0.330	(-0.67)	-	-	-0.162	(-0.34)
Public Utilities	-0.875	(-1.46)	-	-	-0.160	(-0.26)
Wholesale & Retail	0.830	(1.74)	-	-	0.851	(1.81)
Cohorts:						
Issued in 1989	0.989	(2.06)	0.957	(2.13)	1.074	(2.29)
Issued in 1990	-0.185	(-0.29)	0.145	(0.21)	0.093	(0.14)
Issued in 1991	-1.396	(-1.29)	-1.393	(-1.28)	-1.170	(-1.08)
Issued in 1992	0.615	(1.46)	0.629	(1.53)	0.643	(1.53)

Table A-I

The Time structure of Average Hazard Rate using S&P Historical Average Cumulative Default Probabilities

Table 1a describes the historical average cumulative default rates (in percents) of the main rating categories as documented by S&P. Denote by $F_r(T)$ the average cumulative probability of default of rating r from time of rating till time T. Table 1b describes $f_r(T) = F_r(T) - F_r(T-1)$ - the average probability of default of rating r between time $T-1$ and time T. Table 1c describes $\theta_r(T) = f_r(T)/[1 - F_r(T-1)]$ the average hazard rate of default between time $T-1$ and time T.

Table A-I-a – Average cumulative default rate - $F_r(T)$

	Years from rating														
Rating	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
AAA	0.00	0.00	0.03	0.06	0.10	0.18	0.26	0.40	0.45	0.51	0.51	0.51	0.51	0.51	0.51
AA	0.01	0.04	0.09	0.16	0.25	0.37	0.53	0.63	0.70	0.79	0.85	0.92	0.96	1.01	1.07
A	0.04	0.11	0.19	0.32	0.49	0.65	0.83	1.01	1.21	1.41	1.56	1.65	1.70	1.73	1.83
BBB	0.22	0.50	0.79	1.30	1.80	2.29	2.73	3.10	3.39	3.68	3.91	4.05	4.22	4.37	4.48
BB	0.98	2.97	5.35	7.44	9.22	11.11	12.27	13.35	14.29	15.00	15.65	16.00	16.29	16.36	16.36
B	5.30	11.28	15.88	19.10	21.44	23.20	24.77	26.01	26.99	27.88	28.48	28.96	29.34	29.68	29.96
CCC	21.94	29.25	34.37	38.24	42.13	43.62	44.40	44.82	45.74	46.53	46.84	47.21	47.66	48.29	48.29
Investemnt Grade	0.08	0.19	0.31	0.51	0.72	0.95	1.17	1.37	1.54	1.71	1.84	1.93	2.00	2.06	2.14
Speculative Grade	4.14	8.34	11.93	14.67	16.84	18.64	19.98	21.09	22.05	22.85	23.46	23.88	24.22	24.45	24.58

Table A-I-b – Average probability of default - $f_r(T)$

	Years from rating														
Rating	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
AAA	0.00	0.00	0.03	0.03	0.04	0.08	0.08	0.14	0.05	0.06	0.00	0.00	0.00	0.00	0.00
AA	0.01	0.03	0.05	0.07	0.09	0.12	0.16	0.10	0.07	0.09	0.06	0.07	0.04	0.05	0.06
A	0.04	0.07	0.08	0.13	0.17	0.16	0.18	0.18	0.20	0.20	0.15	0.09	0.05	0.03	0.10
BBB	0.22	0.28	0.29	0.51	0.50	0.49	0.44	0.37	0.29	0.29	0.23	0.14	0.17	0.15	0.11
BB	0.98	1.99	2.38	2.09	1.78	1.89	1.16	1.08	0.94	0.71	0.65	0.35	0.29	0.07	0.00
B	5.30	5.98	4.60	3.22	2.34	1.76	1.57	1.24	0.98	0.89	0.60	0.48	0.38	0.34	0.28
CCC	21.94	7.31	5.12	3.87	3.89	1.49	0.78	0.42	0.92	0.79	0.31	0.37	0.45	0.63	0.00
Investemnt Grade	0.08	0.11	0.12	0.20	0.21	0.23	0.22	0.20	0.17	0.17	0.13	0.09	0.07	0.06	0.08
Speculative Grade	4.14	4.20	3.59	2.74	2.17	1.80	1.34	1.11	0.96	0.80	0.61	0.42	0.34	0.23	0.13

Table A-I-c – Average hazard rate of default - $\theta_r(T)$

	Years from rating														
Rating	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
AAA	0.00	0.00	0.03	0.03	0.04	0.08	0.08	0.14	0.05	0.06	0.00	0.00	0.00	0.00	0.00
AA	0.01	0.03	0.05	0.07	0.09	0.12	0.16	0.10	0.07	0.09	0.06	0.07	0.04	0.05	0.06
A	0.04	0.07	0.08	0.13	0.17	0.16	0.18	0.18	0.20	0.20	0.15	0.09	0.05	0.03	0.10
BBB	0.22	0.28	0.29	0.51	0.51	0.50	0.45	0.38	0.30	0.30	0.24	0.15	0.18	0.16	0.12
BB	0.98	2.01	2.45	2.21	1.92	2.08	1.30	1.23	1.08	0.83	0.76	0.41	0.35	0.08	0.00
B	5.30	6.31	5.18	3.83	2.89	2.24	2.04	1.65	1.32	1.22	0.83	0.67	0.53	0.48	0.40
CCC	21.94	9.36	7.24	5.90	6.30	2.57	1.38	0.76	1.67	1.46	0.58	0.70	0.85	1.20	0.00
Investemnt Grade	0.08	0.11	0.12	0.20	0.21	0.23	0.22	0.20	0.17	0.17	0.13	0.09	0.07	0.06	0.08
Speculative Grade	4.14	4.38	3.92	3.11	2.54	2.16	1.65	1.39	1.22	1.03	0.79	0.55	0.45	0.30	0.17

Figures

Figure 1 - Coefficients of Main Categories Ratings

The graph shows the coefficients of the dummy variables for the main rating categories in the second run from table VII - estimation of a proportional hazard function of the form $\theta(T;x_{it},t) = k(x_{it},t) \cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the term structure $k_2(T)$. In this run only dummy variables for S&P main categories rating classifications and dummy variables for the year of issue were used.

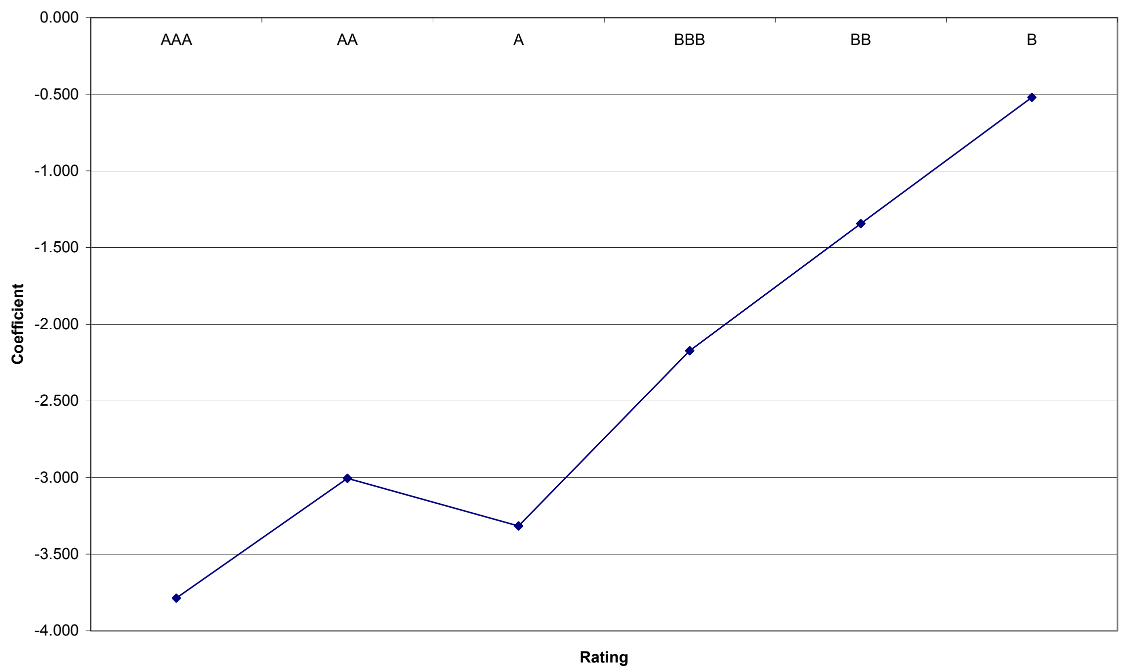


Figure 2 - Coefficients of Sub-Categorized Ratings

The graph shows the coefficients of the dummy variables for the sub-categorized ratings in the second run from table XII - estimation of a proportional hazard function of the form $\theta(T;x_{it},t)=k(x_{it},t)\cdot k_2(T)$. By using a nonparametric approach (Cox maximum partial likelihood), the firms' specific component $k(x_{it},t)$ can be estimated without determining the form of the term structure $k_2(T)$. In this run only dummy variables for S&P sub-categories rating classifications and dummy variables for the year of issue were used.

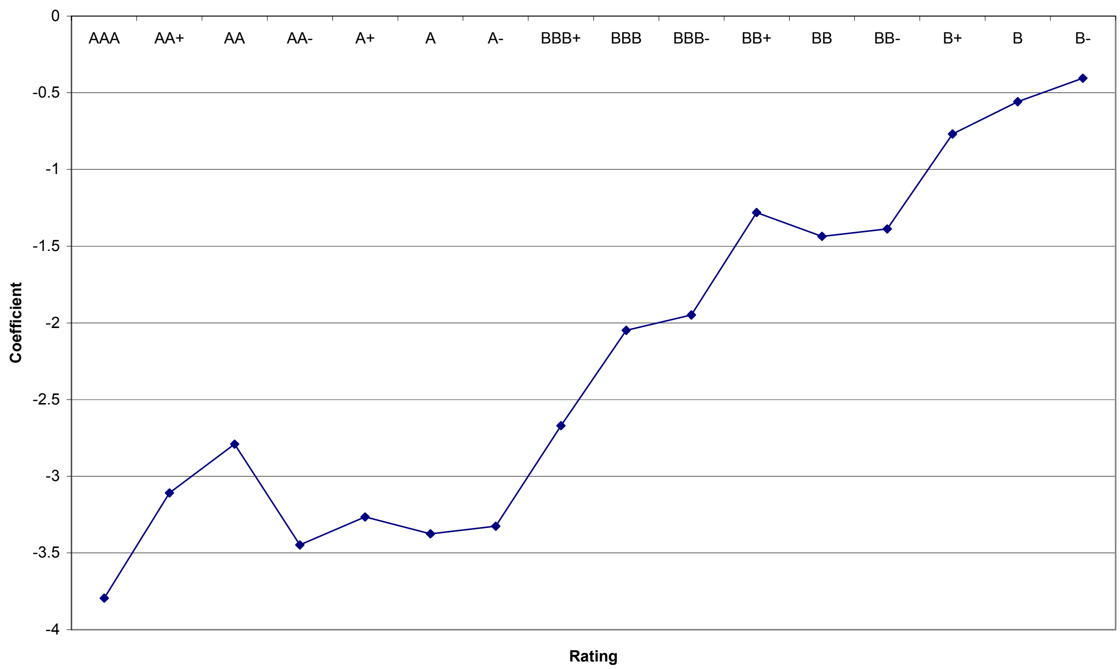


Figure 3 – Log of Average Cumulative Default Rate in 15 Years According to S&P

The graph shows the log of average cumulative default rate in 15 years according to S&P publication - "Ratings Performance 2000".

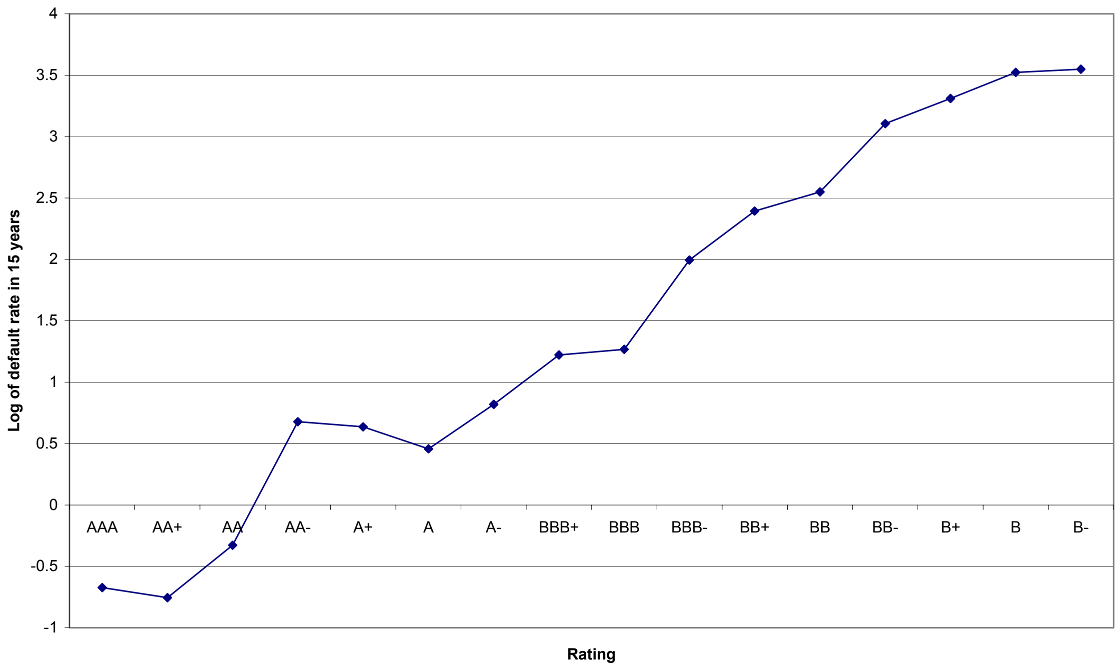
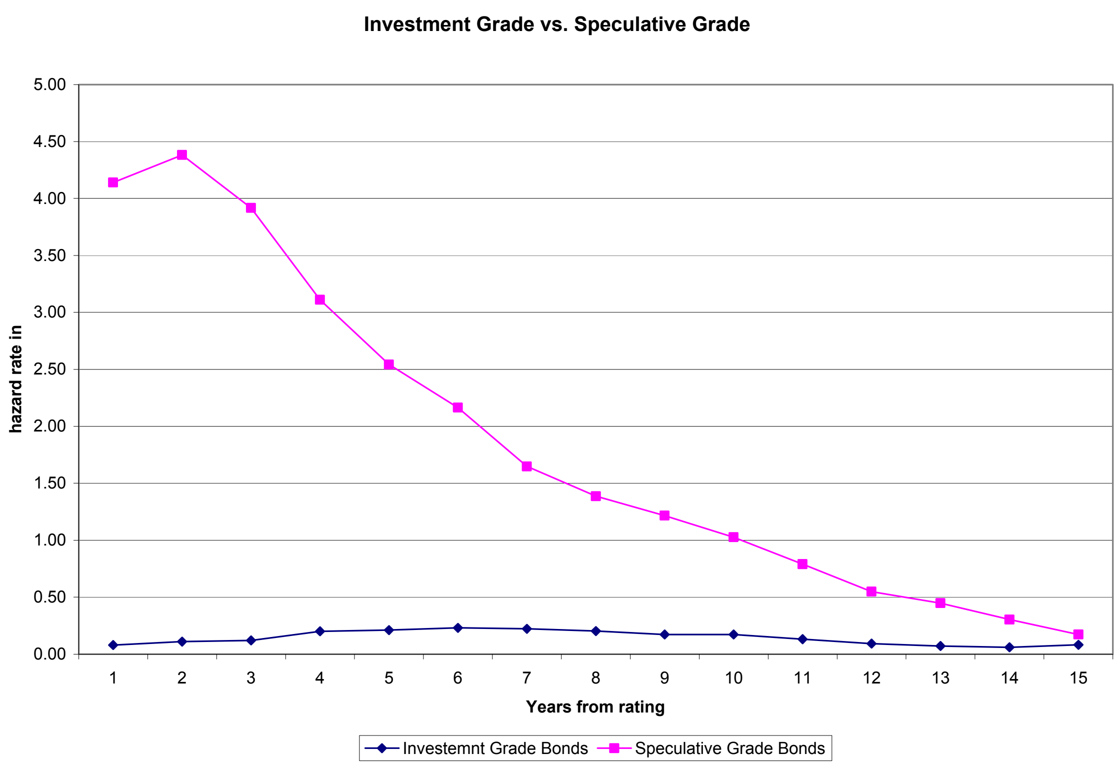


Figure A-1 - The Term Structure of Average Hazard Rate using S&P Historical Average Cumulative Default Probabilities

Figures A-1a to A-1i describe the average hazard rate of default of each rating category as a function of time from rating. These figures are based on average cumulative default probability as documented by S&P.[1] Let $F_r(t)$ denote the average cumulative probability of default of rating r, t years after assigning the rating. Then $f_r(t) = F_r(t) - F_r(t-1)$ denote the average probability of default of rating r between time $t-1$ and time t and $\theta_r(t) = f_r(t)/[1 - F_r(t-1)]$ the average hazard rate of default between time $t-1$ and time t.

Figure A-1a



[1] "Ratings Performance 2000", Standard & Poor's.

Figure A-1b

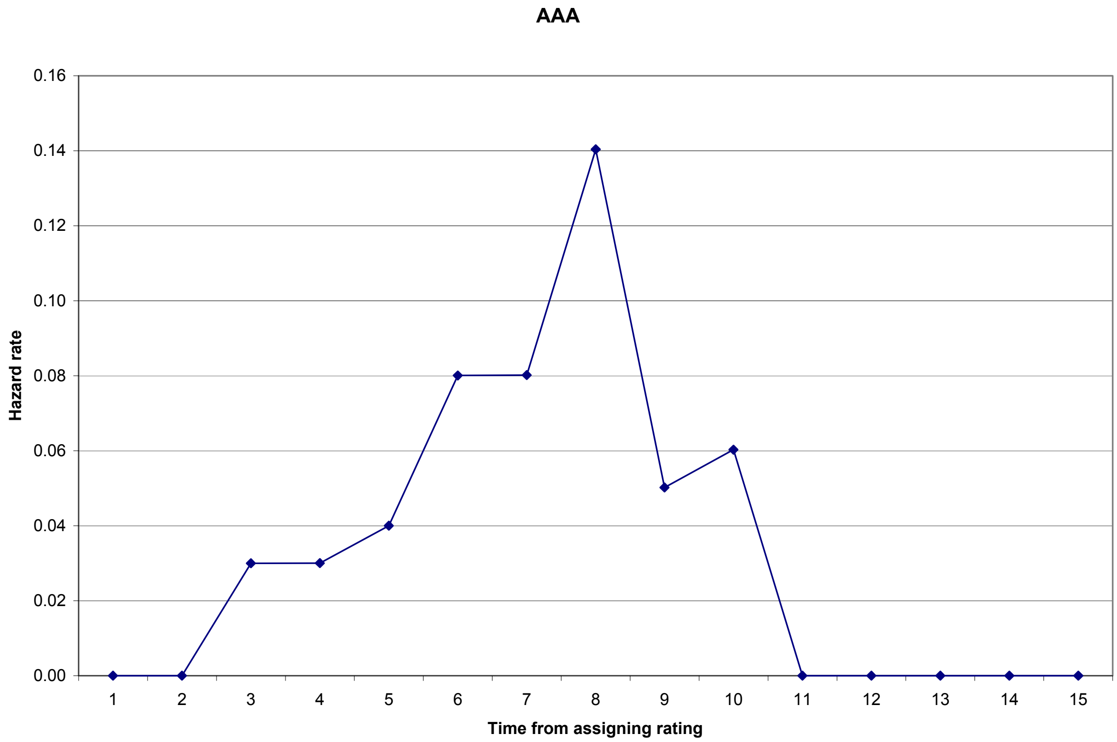


Figure A-1c

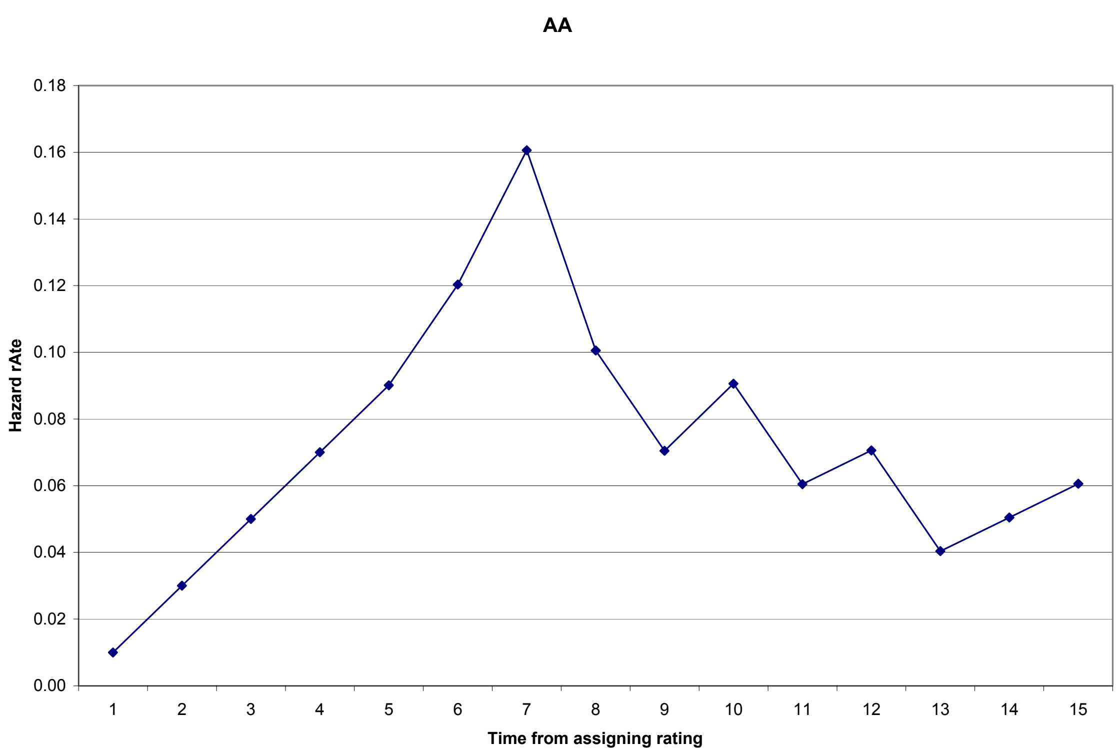


Figure A-1d

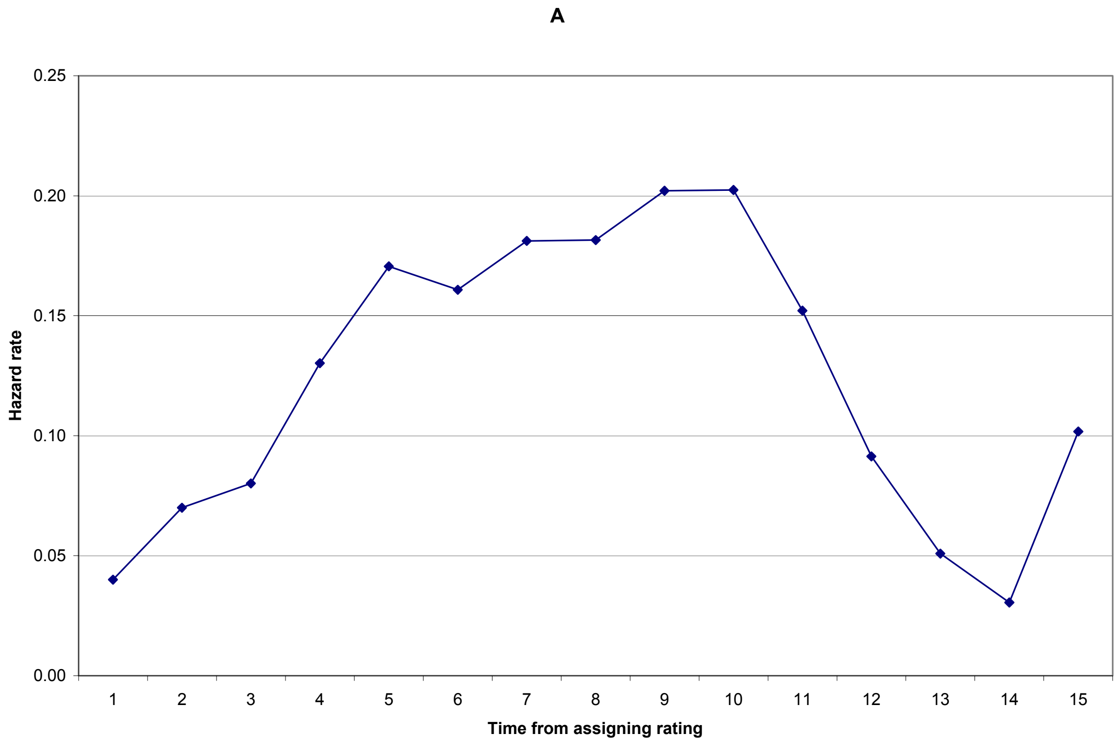


Figure A-1e

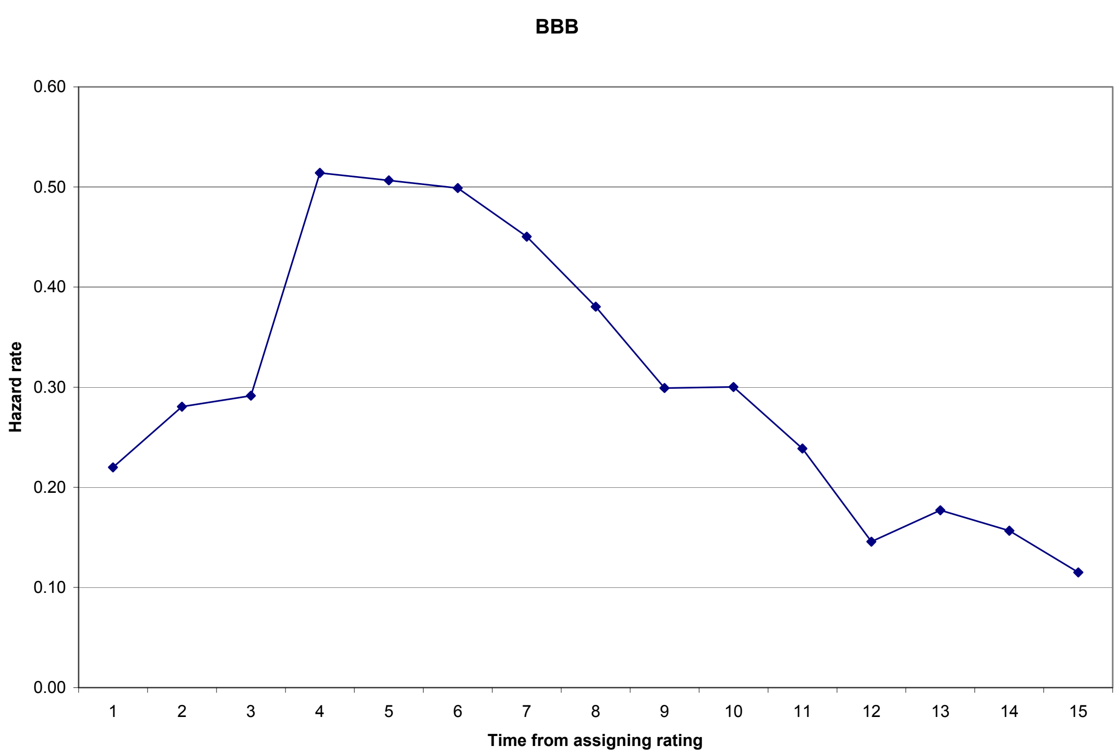


Figure A-1f

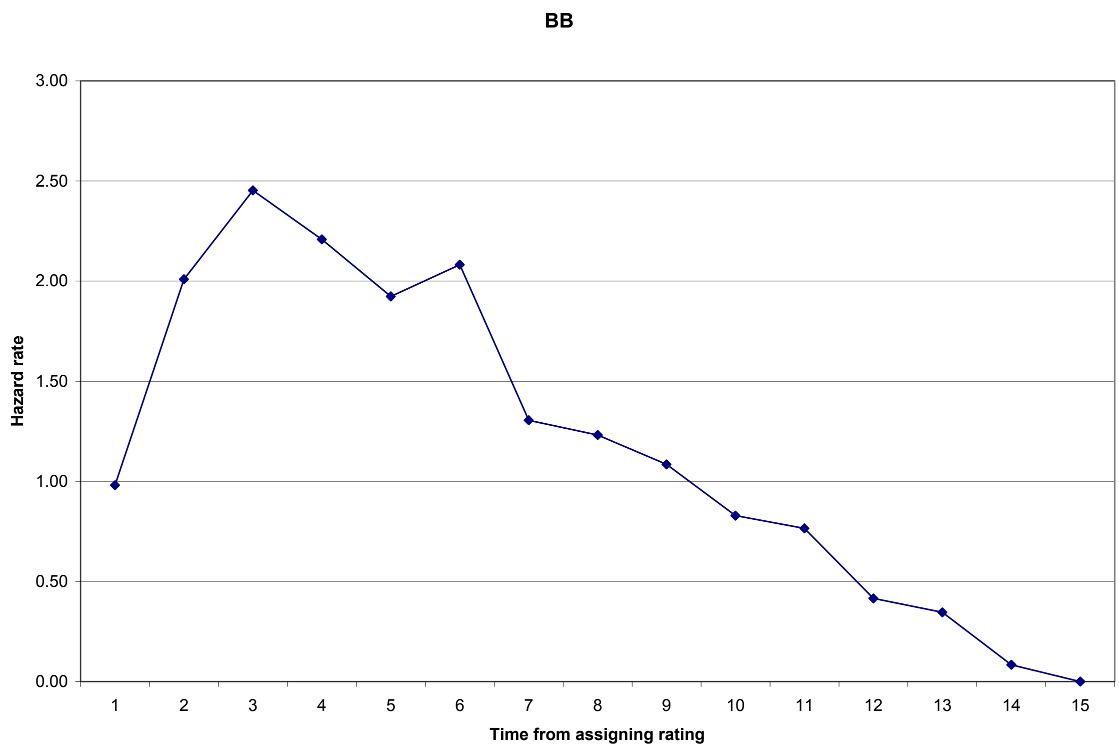


Figure A-1g

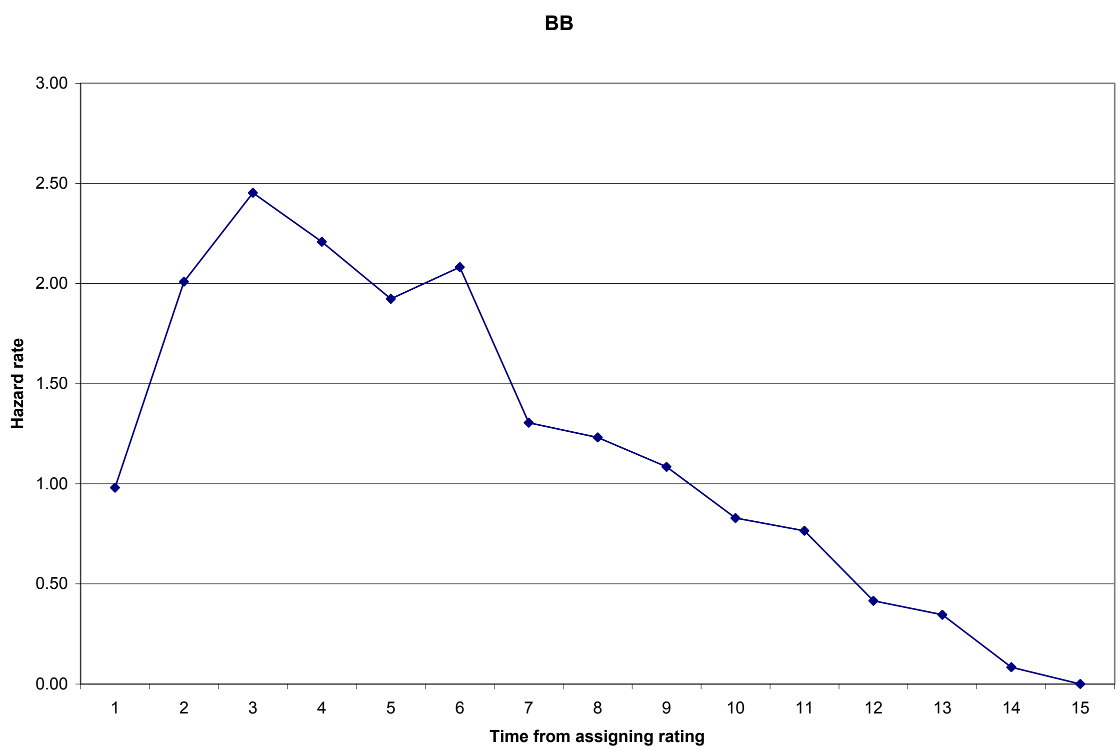


Figure A-1h

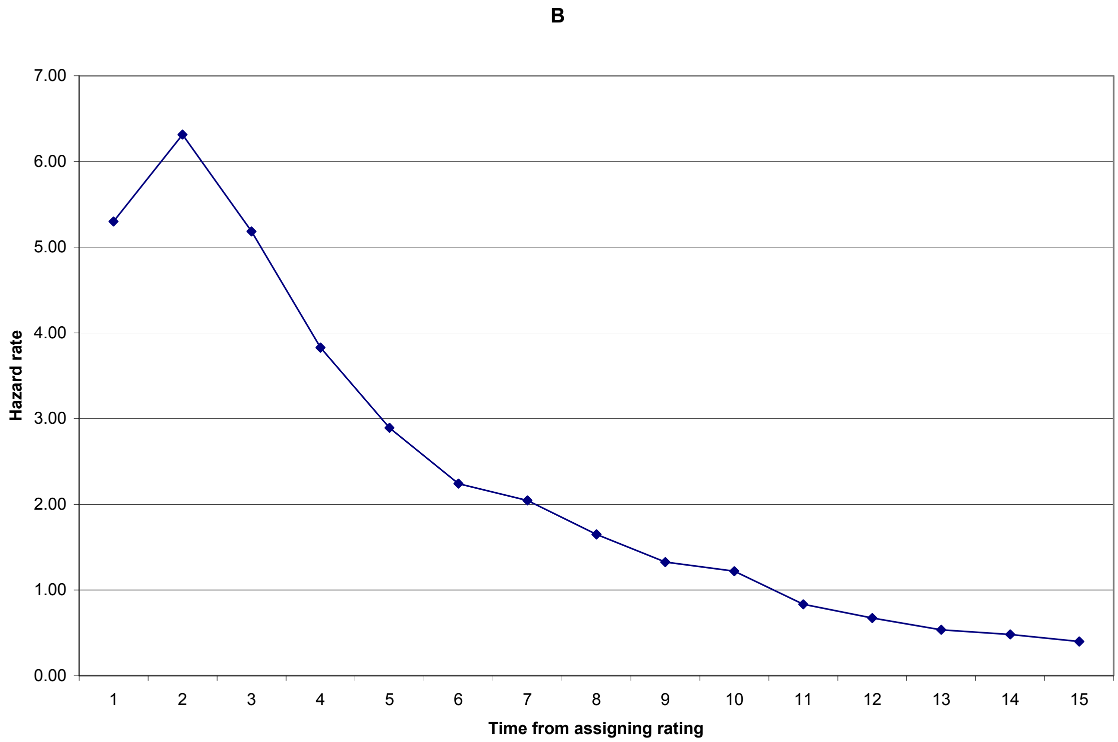


Figure A-1i