Predicting Credit Rating and Credit Rating Changes: A New Approach

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Abstract

In this paper, we propose a hazard rate model for studying credit rating and credit rating changes. Theoretically the hazard rate model is more appropriate than the previous static models. Yet it is difficult to estimate hazard rate model, especially when the covariates are time-varying. This paper extends the results of Shumway(2001) and shows that a multiple-state hazard rate model can be estimated through the standard logistic methods. This finding greatly simplifies the application of hazard rate model to our credit rating studies, and other potential areas. Applying the hazard rate model, we find that: Different from previous findings, the duration effect on credit rating changes is not monotonic. This solves previous conflicting findings on duration effect; Further, we document that duration effect on downgrade is mainly caused by the downgrade momentum effect; We also provide additional support for the argument that credit rating agencies were adapting more stringent rating policy over time, yet this trend broke down around year 1997; Moreover, our empirical results suggest that our hazard rate model does outperform the traditional models in terms of eight predictability measures used in this paper.

Keywords: Credit Risk, Credit Rating, Hazard Rate Model, Logistic Model.

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1 Introduction

Credit rating is the index assigned by rating agencies, such as Moody's and Standard & Poor's, as a measure of creditworthiness and default probability of a rated name. Credit rating plays an important and extensive role in financial markets. With regard to firms seeking financing, few of them would enter corporate debt markets without evaluations from rating agencies. A corporation with a higher rating could get debt for lower cost, and as a result, credit rating is one of the most important considerations when firms decide their corporate policy (See Graham and Harvey, (2001)). From the investors' point of view, they rely on credit ratings to determine their investment policy and the riskiness of their bond portfolio. As for the regulators, Basel Committee suggested using credit ratings as a method in deciding banks' capital reserve. Moreover, with the development of financial innovation, the payoffs of some credit risk derivatives are designed to depend on credit ratings too.

Rating agencies claim that subjective judgement, which cannot be reduced to mathematical formulas, is critical in deciding credit ratings (see Standard & Poor's, 2000). In addition, they claim to have access to superior information that is difficult if not impossible for outsiders to obtain. Consequently, the rating agencies are skeptical about the ability of using some statistical models and publicly available information to capture the professional bond rating process. However, there have been a fair number of studies on credit ratings and the default probabilities of the obligors. Notable published contributions are Horrigan (1966), West (1970,1973), Pogue and Soldofsky (1969), Kaplan and Urwitz (1979), and Blume, Lim and Mackinlay (1998). Despite the skepticism from the rating agencies, these models did well in explaining and predicting the ratings of a large cross section of corporate bonds.

However, the implication of these studies may be limited in many situations of interest.

In many cases, it is important to study the credit rating changes too. Suppose a firm is maintaining a large portfolio of credit risky assets, then the projection of credit rating changes is of interest in order to adjust reserves against the change in the likelihood of portfolio loss. Beyond such a risk management concern, in the financial markets, the payoffs of some derivatives are contingent on the credit rating changes. Derivative subject to credit related barriers is an example of contracts whose payoffs is contingent on a credit event other than default. Total return swap could also establish payout due to credit rating devolution as well as default. When a portfolio is exposed to contingent payments in the event of credit devolution, the study on credit evolutionary path becomes crucially relevant. For example, Jarrow, Land and Turnbull (1997) argues that one of the strengths of their reduced form credit risk model is being able to price credit risk derivatives contingent on credit rating changes.[1]

To the best of our knowledge, there have been only a few recent studies on credit rating changes. Using credit rating data, Lando and Skødeberg (2000),and Kavvathas (2000), estimate the generator of the continuous-time credit rating transition matrix. To improve the explaining and predicting power of their hazard rate models, they included some economic-wide and firm specific factors as independent variables. They found that credit rating changes do not follow Markovian Chain process, as is assumed in the reduced form credit risk model by Jarrow et. al. (1997)[2]. Using a limited dependent variable model, ordered probit model, Nickell, Perraudin and Varotto (2001) studied the stability of credit rating transitions. They found that business cycle, industrial and domicile factors

[1]We should notice that the empirical credit rating migration probabilities are not necessarily equal to the risk neutral ones used for pricing corporate debt. The difference between actual migration probabilities and risk neutral ones reflects risk premium. The mapping between the empirical credit rating transition matrix and the risk neutral one is far from trivial. See Jarrow, et, al (1997) and Duffie and Singleton (2003) for details.

[2]They document that both previous and current ratings account for the rating transition, which is in clear contrast to the definition of Markov Chain. They also find the rating momentum exists, which confirms the results of other studies, such as Carty and Fons (1993).

affect the credit rating transitions. Blume, Lim, and Mackinlay (1998), hereafter BLM, studied a panel data of credit ratings from 1978 to 1995, and suggest that credit rating agencies are employing more and more stringent standards when deciding ratings, rather than that the corporate credit quality has been declining.

Further, most studies on credit rating used static, cross-sectional specifications for credit rating, neglecting the time varying nature of credit rating. In the corporate default literature, Shumway (2001) provided both theoretical arguments and empirical evidence against static models. He argued that the static model estimates are biased, and showed the superior default prediction power of his hazard rate model. The same argument applies to the credit rating literature. By arbitrarily choosing when to observe each firm's characteristics, previous studies introduce an unnecessary selection bias into their estimates. For example, some papers used six years' observations on independent variables immediately before the credit rating observation, while others chose five or three years' data (BLM) to calculate the average. Obviously, different selections generate different estimations. A serious problem with this practice is that during the long window, credit rating may well be different from what we observed at the end of the window. To get a feel for our argument, imagine that we are trying to explain the credit rating at the end of, say, year 1998. Then, according to the above practise, we use, say, five years' (1994 to 1998) average value of some risk factors, say, debt ratio, as the independent variables. But the problem is if a particular firm had been in a different credit rating since 1994, and only migrated in, say *July* 1998, to the current rating, then the model is actually explaining the credit rating in *July* 1998 rather than that of December 1998, because five years' average is more relevant to the credit rating of *July* 1998, not that of December 1998. Consequently, inconsistence would arise in the estimations by neglecting the time-varying nature of credit ratings and firms' characteristics. Having realized this problem, some authors chose observations whose credit rating did not change during a certain period of time, say, from the beginning of 1997 to the end of 1998 (See Kaplan and Urwitx, 1979). Yet not only can it eliminate this bias, but also it introduces another bias. As we will see, the length of time of being in the current rating is a significant factor affecting the credit rating changes. So, restricting their sample to those cross-sectional units with durations of at least 12 months would cause biased estimations.

In contrast, by utilizing the whole history of cross-sectional units, hazard rate models explicitly consider the time-varying nature of both the credit rating and firm's characteristics. Shumway (2001) demonstrated the superior default forecasting power of hazard rate model over traditional models. His study has been confirmed by Hillegeist, et. al. (2002), and Chava and Jarrow (2002). However, although theoretically appealing, hazard rate model with time varying covariates is very difficult to estimate. Shumway (2001) showed the equivalence between the hazard rate model and dynamic binary logistic model in terms of the likelihood function. This observation greatly simplifies the estimation and econometric inference of hazard rate models with time varying covariates because it is easy to estimate logistic models. In this paper, we extend the results of Shumway (2001) from binary setting to the multiple case, and propose a dynamic multi-nomial logistic model. Taking advantage of the flexibility of our model, we find that: Different from previous findings, the duration effect on credit rating changes is not monotonic. This solves previous conflicting findings on duration effect; Further, we document that duration effect on downgrade is mainly brought about by the downgrade momentum effect; We also provide additional support for the argument that credit rating agencies were adapting more stringent rating policy over time, yet this trend broke down around year 1997; Moreover, our empirical results suggest that the hazard rate model does outperform the traditional models in terms of eight predictability measures used in this paper.

The remainder of this paper is organized as follows. Section 2 develops a dynamic multi-nomial multi-cycle logistic model, and proves the similarity between the dynamic logistic model and the hazard rate model . Section 3 presents the procedure of data collection. Section 4 describes the empirical tests, and discusses the estimation results. In addition, forecasting abilities of the hazard rate model and traditional model are investigated. Section 5 makes the concluding remarks.

2 Hazard Rate Model Vs. Dynamic Multi-nomial Logistic Model

In this section, we first briefly introduce the basic concept of the simplest logistic models and hazard rate (duration) models. Then, we show the similarity between hazard rate model and dynamic multi-nomial logistic model in terms of log-likelihood functions.

2.1 Introduction to Logistic Models and Hazard Rate Models

Since the dependent variable, credit rating, is a qualitative variable in nature, *OLS*, which assumes that the regressand is quantitative and continuous, is not appropriate for credit rating. A *logistic* type of limited dependent variable model addresses this problem by linking the observed qualitative variable, the credit ratings, with the unobserved credit quality, which is affected by the covariates included in the model. It works as follows:

Let Y_i be the rating of firm i, which are determined by the realization of latent random credit quality Z_i. This variable is in turn governed by X_i:

$$Z_i = \beta X_i + \epsilon_i \tag{1}$$

where X_i represents all the information of firm i up to current time, and β are the regression coefficients to be estimated. Assume there are K different credit ratings in total. Logistic models assume that Y_i is determined in the following way:

$$Y_i = \begin{cases} 1 & \text{if } Z_i \leq \mu_1 \\ 2 & \text{if } \mu_1 < Z_i \leq \mu_2 \\ \ldots & \ldots \\ K & \text{if } \mu_{K-1} < Z_i \end{cases} \tag{2}$$

Here μ_i, called the cut-off points, are unknown parameters that collectively define a series of ranges into which the latent variable may fall. The value of those cut-off points will be estimated with β simultaneously. If we assume ϵ follows a particular distribution, then it is straightforward to employ the maximum likelihood technique to estimate this model. For example, probit models assumes that is normally distributed, while logistic models admit logistic distribution. For the probit model, we have the following probabilities:

$$\begin{aligned} &\mathrm{Prob}(\mathrm{Y}_i = 1) = \Phi(\mu_1 - \beta X_i), \\ &\mathrm{Prob}(\mathrm{Y}_i = 2) = \Phi(\mu_2 - \beta X_i) - \Phi(\mu_1 - \beta X_i), \\ &\quad\vdots \\ &\mathrm{Prob}(\mathrm{Y}_i = K) = \Phi(\mu_{K-1} - \beta X_i). \end{aligned}$$

For all the probabilities to be postitive, we must have:

$$\mu_1 < \mu_1 < \mu_2 < \ldots < \mu_{K-1}.$$

Let us define an indicator function d_l, which equals one if firm's credit rating is l and zero otherwise. Then the likelihood function of the logistic model takes the following form:

$$\ell = \prod_{i=1}^{N} \prod_{l=1}^{K} \mathrm{Prob}(\mathrm{Y}_i = l)^{d_l}. \tag{3}$$

Let T be a positive, continuous random variable representing the time to exit from a given credit rating. In this study, it represents the time when a firm transfers from a particular credit rating to another, say, from AA to BBB. The hazard function at time

t is defined as the conditional probability of exiting the current credit rating, given it stay at the current rating up to time t:

$$\theta(t, X) = \lim_{\Delta s \to 0} \frac{\text{Prob}(t \leq T < t + \Delta s \mid T \geq t)}{\Delta s} \tag{4}$$

We allow for the influence of observable individual heterogeneity on the hazard rates through the observable covariates, x, which may be time-varying. More specifically, the hazard rate θ is allowed to differ across individuals through a parameterization that depends on x. By the standard manipulation, the survivor function associated with this specification can be derived as[3]:

$$S(t, x) = \text{Prob}(T \geq t) = \exp(-\int_0^t \theta(u, x) du),$$

with the density function being:

$$f(t, x) = \frac{\theta(t, x)}{S(t, x)}. \tag{5}$$

In order to perform maximum likelihood estimation, distribution assumptions have to be made. Popular choices include exponential distribution, Weilbull distribution, log-normal distribution, and loglogistic distribution.

In many cases including credit rating, when a cross-sectional unit left its current state, it has multiple destinations to go to. For example, a firm's credit rating can be changed to any other ratings ranging from AAA to C, if it experiences rating migration. We call a hazard rate model with multiple destinations a multi-nomial hazard rate model to differentiate it from the bi-nomial hazard rate model. In the multi-nomial hazard rate models, the hazard function of departure to state k at time t is given as θ_k. Hence $\theta_k dt$ gives the probability of departure to k at time t conditional on staying in the current state up to time t. By standard arguments, the survivor function is:

$$S(t, x) = \text{Prob}(T \geq t) = \exp\Big(-\int_0^t \sum_{k=1}^{K} \theta_k(u, x) du\Big) \tag{6}$$

[3]We do not require that the observations at different points of time are independent. This point is critical in understanding our arguments in our estimation and inference section.

Define indicator $d_{t,k}$, which equals 1 if the firm departs to state k at time t, 0 otherwise. Then the *unconditional* probability of leaving for state k at time t can be written:

$$\text{Prob}(d_{t,k} = 1) = \theta_k(t,x)\text{exp}\Big(- \int_0^t \sum_{k=1}^{K} \theta_k(u,x)du\Big)dt, \tag{7}$$

or:

$$p(\mathbf{d},t) = \text{exp}\Big(\sum_{k=1}^{K} \Big[d_k \text{log}\theta_k(t,x) - \int_0^t \theta_k(u,x)du \Big] \Big), \tag{8}$$

which is a particular firm's contribution to the likelihood function. Here, $\mathbf{d}$ denotes the vector of $d_{t,k}$.

2.2 Model Setting

Now we turn to the dynamic setting. We assume that credit rating migration can happen at any of the following discrete times, $t = t_0 + \Delta s, t_0 + 2\Delta s, t_0 + 3\Delta s, \ldots$. Δs can be very small to approximate the continuous time setting. Further, we use T_i to represent the time when firm i leaves our sample.[4] And we let the probability of transition from credit rating l to rating m at time $t + s$ be given by $P_{lm}(t,x,s)$, where s measures the duration that rating l has been continuously occupied up to since it was entered at time t. x represents the independent variables, or the covariates, which may be time-varying. *Duration* is a central element in hazard rate models. That's why sometimes people interchange hazard rate model with *duration model*.

Now let us describe hazard rate models. Following the hazard rate model convention, we let $\theta_{lm}(t,x,s)$ represent transition intensity from rating l to rating m, given that state l was entered at time t and has been occupied up to time $t+s$, where x, as usual, represents a vector of independent variables. So, $\theta_{lm}(t,x,s)\Delta s$ gives the probability of, at time $t+s$,a departure to state m in the short interval from $t+s$ to $t+s+\Delta s$. This probability is conditional on occupation of credit rating l for s period of time since time

[4]For ease of notation, I omit the subscript i later on.

t, and upon the previous transition history. Further, we let c indicate the c'th cycle[5] of the rating migrations process, with the total number of cycles being C.[6] In addition, we let S_c be the duration of c'th cycle. Rating migration only occurs at the end of each cycle. Also, we define a binary indicator d_{cm}, which equals 1 if rating m is entered at the *end* of the c'th cycle, and 0 otherwise.

2.3 Proof of the Equivalence

Shumway (2001) model is the simplest hazard rate model. Specifically, there are only two states in his model: default and not default. Further, if a firm defaults, it will be deleted from the data sample. So Shumway (2001) model is a binary-single-cycle hazard rate model. This model is appropriate for bankruptcy studies. However, as for credit rating, each firm has multiple destinations to go when it experiences rating change. For example, its rating can transfer from AAA to AA, or BB, or CC, or even default. In addition, each firm can experiences multiple rating migrations during a particular period of time. In this section, we extend the Shumway's binary-single cycle hazard rate model to the multi-nomial multi-period case, and show the equivalence of the hazard rate model and the dynamic logistic model. By equivalence, we mean that their likelihood functions are identical. So are the estimates.

Proposition *A multi-period multi-nomial logistic model is equivalent to a hazard rate model with hazard function* $P_{lm}(t, x, s)/\Delta s$.

Proof:

[5]Each cycle begins when the firm enters a new credit rating, and ends when it migrates to another rating.

[6]During the life of a firm, its credit rating may transit multiple times.

A multiperiod multi-nomial logistic model is estimated with each panel data point, say each firm-year as if it were a separate observation. So, the contribution of a specific firm i to the likelihood function during its cycle in the sample, is as follows:[7]

$$\ell = \prod_{c=1}^{C} \prod_{l=1}^{K} \Big([\prod_{s_c=0}^{S_c} P_{ll}(t_c, x, s_c)]^{d_{c-1,l}} \prod_{m=1}^{K} P_{lm}(t_c, x, S_c)^{d_{c,m} d_{c-1,l}} \Big); \quad l \neq m, \tag{9}$$

The S_c is the completed duration of cycle c, and the t_c is the calendar time at which the c' th cycle was commenced. Recall credit rating changes only happen at the end of each cycle after a rating was entered.

Because Δs is a constant, we can divide equation(9) by polynomials of Δs, without changing the maximum likelihood estimation results. Then we have:

$$\ell' = \prod_{c=1}^{C} \prod_{l=1}^{K} \Big([\prod_{s_c=0}^{S_c} P_{ll}(t_c, x, s_c)]^{d_{c-1,l}} \prod_{m=1}^{K} \Big[\frac{P_{lm}(t_c, x, S_c)}{\Delta s} \Big]^{d_{c,m} d_{c-1,l}} \Big); \quad l \neq m, \tag{10}$$

So we get the following loglikelihood function:

$$L = \sum_{c=1}^{C} \sum_{l=1}^{K} \Big[\sum_{m=1}^{K} d_{c-1,l} d_{c,m} \log \Big[\frac{P_{lm}(t_c, x, S_c)}{\Delta s} \Big] + d_{c-1,l} \log \prod_{s_c=0}^{S_c} P_{ll}(t_c, x, s_c) \Big], \quad l \neq m \tag{11}$$

Let $P_{lm}(t_c, x, s_c) = \theta_{lm}(t_c, x, s_c) \Delta s$. And recall[8]

$$\prod_{s_c=0}^{S_c} P_{ll}(t_c, x, s_c) \approx \exp[- \int_0^{S_c} \sum_{m=1}^{K} \theta_{lm}(t_c, x, u) du] \quad l \neq m \tag{12}$$

Then we arrive:

$$L = \sum_{c=1}^{C} \sum_{l=1}^{K} \Big[\sum_{m=1}^{K} d_{c-1,l} d_{c,m} \log \theta_{lm}(t_c, x, S_c) - d_{c-1,l} \int_0^{S_c} \sum_{m=1}^{K} \theta_{lm}(t, x, u) du \Big] \quad l \neq m, \tag{13}$$

[7] Equation (9) is very intuitive. In its life cycle, a firm could transit within all possible credit rating states, including going bankruptcy, or stay in its original rating. So, the likelihood contributed by any specific firm is the product of the transition probabilities and/or the probability of staying in its original rating. For example, suppose a firm's rating at time t_0 was AAA, and time $t_0 + \Delta s$ it was downgraded to AA, then it went to B at time $t_0 + 2\Delta s$, and stayed in rating B ever since, then the likelihood function contributed by this firm is $P_{AAA,AA}(\cdot) P_{AA,B}(\cdot) P_{B,B}(\cdot)$. An implicit reasonable assumption made here is that the latent variable solely determines the credit rating migration probability.

[8] $\prod_{s_c=0}^{S_c} P_{ll}(t_c, x, s_c)$ is approximately the survivor function. See Gourieroux (2000) for rigorous mathematical proof of equation (12) .

Rearrange the terms, we have:

$$L = \sum_{c=1}^{C} \sum_{l=1}^{K} \sum_{m=1}^{K} d_{c-1,l} \Big[d_{c,m} \log \theta_{lm}(t_c, x, S_c;) - z_{lm}((t_c, x, S_c;) \Big], \tag{14}$$

where

$$z_{lm}(t_c, x, S_c;) = \int_0^{S_c} \theta_{lm}(t_c, u) du; \quad l, m = 1, 2, \ldots K, l \neq m.$$

Equation (14) is exactly the likelihood function for multi-period, multi-nomial hazard rate model presented in Lancaster (1990). So, if we let the probability density function of transition from credit rating l to rating m be given by $P_{lm}/\Delta s$, the likelihood function of a multiperiod logistic model is equivalent to the likelihood function of a discrete-time hazard rate model.

QED.

2.4 Estimation and Inference of Hazard Rate Models

Given the data on grouped durations, the logistic and the hazard rate models (Duration models) are completely specified through parameterization of the transfer function and hazard functions. Thus, any issues associated with duration dependence and the effects of covariates on hazard rates are embodied in the specification for the functional form of them, as well as how these conditional survivor functions vary over time. Given the framework outlined above, it is easy to analyze the characteristics of hazard specifications implied by the standard logistic models, and to build specifications which admit various forms of duration dependence and covariates effects through flexibility in the specification of the transfer function and the associated coefficients. Any function of duration can be included in the model. This makes our hazard model more flexible than the commonly used parametric models, such as the Weilbull hazard function and log-logistic hazard function. In addition, it is impossible to include time dummies in the traditional duration model. But it is routine to study the dummies variables using our model.

Making statistical inferences in a hazard model estimated with a logistic program is easy. Since the dynamic logistic and hazard models have the same likelihood function, they have the same asymptotic covariance matrix. The χ^2 test statistics provided by the logistic program take the following form:

$$\frac{1}{n}(\hat{\mu_k} - \mu_0)'\Sigma^{-1}(\hat{\mu_k} - \mu_0) \sim \chi^2(k), \tag{15}$$

where there are k estimated moments being tested against k null hypotheses, μ_0. Basically for hazard rate model, each firm's entire life span is only one observation. Yet when we estimate the dynamic logistic models, the sample size is the total number of firm-time observations, i.e. each firms contributes multiple observations, and time series observations of a particular firm cannot be independent. So Shumway (2001) argues that in order to get the correct inference from the logistic estimations for the hazard rate model, it is necessary to divide the reported test statistics by the average number of firm-years per firms. However, as we have emphasized earlier, hazard rate model does not require firm-year observation independence, although when estimating the logistic model, we do require the independence between the observations. So it is not necessary to make any adjustments to the test statistics. Our argument is consistent with Chava and Jarrow (2002). Indeed, in an empirical paper on personal bankruptcy, Jiang (2003) reported very similar estimation results of the Cox semi-nonparametric duration method and the dynamic logistic method without adjustments, with the relative difference being well below 1%. So, it is valid to directly use the statistics reported by logistic software for the inference purpose. [9]

[9] All the estimations in this paper are conducted using SAS.

3 Data Description

Our data include credit ratings, accounting information, and market information. In this section, we describe our data collection and manipulation process in details.

3.1 Credit Rating and Duration Data

Credit ratings of each corporation, instead of a particular debt, are obtained from the 2002 annual COMPUSTAT, which contains monthly corporate rating data from 1985 to 2002. Rather than using the finer credit ratings provided by S&P, we follow the conventions of previous studies on credit rating and classify all the ratings into the following eight categories: AAA, AA, A, BBB, BB, B, CCC, CC, and Default. One of the advantages of using corporate ratings over individual issue ratings is that any corporate rating changes will reflect changes in the financial and business situations of the firm, rather than changes in indenture provisions. Further, cross default clauses in debt contracts usually ensure that the default probabilities for each of the classes of debt for a firm are the same. That is, the default probability of the firm determines the default probability for all of the firms' debt or counterparts obligations. We collect monthly credit rating data for all firms which had issuer credit ratings by S&P at the end of year 1988. Year 1988 is chosen as the compromise result of two conflicting important requirements. Generally, there are more and more firms rated by S&P over time. So, in order to include more cross-sectional firms, it is desirable to begin with a later year. At the same time, we would like to have long time-series data for each cross-sectional unit. After checking, we decided year 1988 can meet both of the two conflicting requirements. There are 1508 firms in total. The individual firms are then followed from year 1988 to year 2001[10]. Thus, we are examining the relatively much more complete history of firms than other studies did. These data have a number of unique advantages compared to traditional datasets used in other studies. First, the long time series makes it possible

[10]Some firms may leave our sample before 2001, because of default or their ratings being withdrawn.

to estimate explicitly dynamic models of credit changes. Second, the much larger data sets enable us to examine the low probability events like bankruptcy and credit rating changes. Table 1 and Table 2 present the summary information of the monthly credit rating data in each year for each rating.

Each year, there are new firms assigned credit ratings by S&P. So another way to collect data is to include these new issues. But, as observed by Altman (1983, 1998), there are distinctions between new issues and seasoned issues: Older issues appear to have a greater short-term tendency to be upgraded or downgraded than do newly issued bonds. So, in order to eliminate the aging effect brought about by including new issues, we use the first method to collect the credit rating data[11].

Theoretically it is preferable to use the continuous observation of credit ratings (Lando and Skødeberg, (2000)). For example, from t to $t+1$, if a transition from time i to j does not occur, the estimate of the corresponding transition probability is 0. But it may well be that a name transits to a third rating, say m, and then migrates from m to j during the period from time t through $t+1$. So, continuous time data will yield more accurate estimations. However credit rating changes are infrequent for a specific firm. In particular, it is rare to observe multiple migrations in a relatively short period of time. For this reason, it is not unreasonable to use monthly observations to approximate the continuous data.

To carry out empirical analysis, we first calculate the duration, for each firm at each month from December 1988 to Oct 2002, $duration_{i,t}$, using the monthly credit rating data. Here duration is defined as the length of time that the current credit rating has

[11] *Aging effect* is different from the duration dependence effect documented in this paper. Duration dependence concerns how long a firm has been in the *current rating*, while aging effect depends on whether a firm is newly rated or not.

been occupied. For example, suppose a firm's rating transferred to AA at the end of December 1997, and it had stayed in AA since then, its duration at December 1998 is 12 months. Note the duration defined in this paper is different from the aging effect documented by Altman (1983, 1998). Aging effect concerns whether a firm is newly rated or not. Because our credit rating data begin in December 1985,[12] the durations for the earlier months are censored. In particular, a firm's rating may have been in the current rating even before 1985, but we only suppose it entered the current rating in 1985. However this is not a serious concern for two reasons: First, with time going on, most firms would change their ratings sooner or later. Second, by the end of 1988 only 40% of the firms in our sample had not had their ratings changed. The percentage decreased to around 30% at the end of 1989, to about 25% at the end of 1990, and to 15% at the end of 1995.

Our interest is to study the effects of the duration *before* the credit rating change on the credit rating migration probabilities. Table 3 presents the summary statistics of our monthly credit rating duration data. There are two notable observations from Table 3: First, the means of duration decrease with the decline of credit quality, with the minor exception of rating B. This is not surprising. We know that higher credit ratings are characterized by lower transferring probabilities. And according to the standard arguments in stochastic process theory, the larger the probability of staying in the current state, the longer the expected duration will be. The second observation is that standard deviation is an increasing function of credit quality, which is due to the large durations of high quality units.

[12]The earliest issuers credit rating data in 2002 COMPUSTAT begin with December 1985.

3.2 Accounting Information Data

As stated by credit rating agencies, both the business risk and the financial risk of a firm affect credit ratings, and there are no specific mathematical or statistic models to assign ratings (See Standard and Poor's, (2000)). Nevertheless, they do publish some financial ratios that are key elements in its analysis of credit quality. These ratios measure profitability, interest coverage, and leverage. In this section, we describe the data collecting process of the accounting ratios used in this study.

The specific accounting ratios employed in this paper are the same as those in BLM. They include: pretax interest coverage ratio, operating income to sales, long term debt to assets, and total liability to asset[13]. Theoretically, the first two ratios should have positive effects on the credit ratings, while the last two ratios should have negative effects on obtaining higher credit ratings. BLM also includes market value of equity, market model beta, and standard error of market model as independent variables. We will describe them in the next section.

The accounting data were obtained from the 2002 annual COMPUSTAT database. We note that the fiscal year and calendar year of many firms are not necessarily the same. For example, suppose a firm's fiscal year-end is May 1997. Then, if we evaluate accounting information from the annual report for year 1997, we will end up with seven of the 12 months from the year 1996. COMPUSTAT employs a systematic way to assign the calendar year into fiscal year. In order to match accounting data with credit ratings, and enable us to have meaningful explanation for year dummies, we employ calendar

[13]Following BLM, the pretax interest coverage is defined as the [operating income after depreciation (178) + interest expense (15)] to [interest expense (15)], where the numbers in parentheses are the COMPUSTAT item numbers. The ratio of operating income to sales is defined as [operating income before depreciation (13)] to [sales (12)]. The ratio of long term debt to assets is defined as [long term debt-total (9)] to [assets-total (6)]. The ratio of total debt to capitialization is defined as [Liability-total (181)] to [assets-total (6)].

year data rather than fiscal year data.

3.3 Market Information Data

Many studies found a positive relation between credit ratings and firms' market value. Therefore, market value is included in our hazard rate model. BLM argues that larger firms tend to have established product lines, and tend to be diversified. Consequently, larger firms would tend to receive a higher credit rating. Another possible institutional explanation is that large firms tend to have easier access to capital markets, so they are more likely to get the money needed to get through financial difficulties. Theoretically, market value is the residual value of firm's total asset value. Consequently, it follows that market expects firms with large market value are not only able to pay back their debt, but also have large residual value left for shareholders.

Theoretically, corporate debt can be regarded as a risk free asset less a put option, namely the equity. Since option value increases with volatility, it follows that increased volatility will increase the default probability. Therefore assets' volatility will be included as an independent variable. The volatility of firm's asset is not readily available. We use the volatility of equity return to approximate the volatility of firms' asset. Campbell and Taksler (2002) have provided empirical evidence supporting this arrangement. Indeed, ceteris paribus, the larger the equity volatility, the large the asset volatility will be[14]. Equity volatility can be classified into systematic risk and unsystematic risk. BLM argues that separating equity risk into beta and non-beta risk allows for the possibility that these two different risk measures might be related to the credit ratings in different ways. Consequently, the composition of systematic and unsystematic risk might con-

[14]We can empirically estimate the volatility for return historical volatility is backward looking. In theory, implied volatility of options written on a particular firm's asset is forward looking, therefore more relevant for our studies. Unfortunately, most of the firms we investigate lack publicly traded options.

vey additional information. Some papers empirically document the association between credit rating and market betas. Yet rating agencies tend to pay more attention to the firms' idiosyncratic risk so that a firm specific risk measure may capture more of the credit rating decision than the systematic risk (See Standard and Poor's, 2000). So, we expect that unsystematic risk is more important.[15]

Moreover, we note that previous papers employed firm's equity return, to proxy for firm's overall health and firm specific risk. Intuitively, the higher the equity return, the higher credit rating would be expected[16]. Sum of 12 months' excess returns is used to represent the equity return for each firm year. CRSP monthly stock returns are used to estimate the market models. The market portfolio return is approximated by the CRSP value-weighted return. We estimate the market model for each firm each year from year 1989 to 2002.

Take year 1993 for example. The time convention used in merging market data, accounting ratios and credit ratings is as follows: The credit ratings and market values are those for year-end 1993; the market model is estimated with the stock returns in 1993; and the accounting ratios are calculated from the 1993 calendar year financial statements rather than that of fiscal year 1993. Furthermore, after checking the original data, we find some observations have extraordinary values. For example, the unreported summary statis-

[15] An alternative method is to obtain the volatility of excess stock market returns. First we calculate monthly excess equity returns relative to the CRSP value-weighted index returns. Then, based on excess returns, we calculate the standard deviation of excess returns for each firm year. In this way, we implicitly impose a beta of one in the market model. Campbell, Lo, and MacKinlay (1996) call this *market adjusted model*.

[16] Actually, the relationship between equity return and credit risk is very complex. The Bondholder Wealth Expropriation Hypothesis predicts that leverage increases induce wealth transfers from bondholder to shareholders. In particular, increased leverage, i.e. credit risk, would be accompanied by positive equity returns. On the other hand, signalling theory says that increasing leverage reflects the confidence of managers, who are considered to be insiders having more information about the health and future perspective of firms than outsiders do. Consequently, the equity market would react positively to the increased credit risk. Therefore the overall relationship between equity return and credit ratings is hard to predict.

tics without truncating show that the maximum interest coverage is 29904.00, with the minimum being -120.99, and the maximum sum of squared residual, hereafter SSR, is 249.43. In order to reduce the effect from those outliers (or typos), we truncate all the variables at the 99th and 1st percentiles. Table 4 presents the summary statistics for the covariates.

4 Empirical Analysis

In this section, we study the effect on the credit rating of various factors. It will be helpful to begin with a simplest specification. Logistic models of credit rating changes were first estimated with only the time dummies and the forth-order polynomial in duration, namely, $Duration, Duration^2, Duration^3$, and $Duration^4$, in the current credit ratings as the independent variables.

4.1 Duration Effect on Credit Rating Changes

A few papers, including Carty and Fons (1993), Lando and Skødeberg (2000) and Kavathas (2000), documented the duration dependence effect on the credit rating migration probabilities. However, their empirical results are conflicting. Lando and Skødeberg (2000) documented that the hazard rate is negatively affected by a change in the duration; i.e. the longer the firm has been in the rating class, the smaller the probabilities it will be upgraded. This is called positive duration dependence in econometric literature. In contrast, Kavathas documented negative duration dependence. He found that both downgrade and upgrade intensities are characterized by an increasing hazard rate for all credit ratings, except that CCC rated issuers have decreasing downgrade intensity. One reason for the conflicting findings, may be due to the different data sets used by those authors. Another reason, perhaps the most important reason, is the strictness of

Weibull distribution[17] functions, which can only identify monotonic duration dependence or none-duration dependence. Specifically, if the shape parameter of Weilbull distribution is 1, then it means there is no duration dependence. Put another way, duration has no influence on the credit migration probabilities; If the parameter is greater than 1, then it follows that the longer the duration the larger the transferring probability would be. And in the last case, the longer the duration, the smaller the probabilities would be, when the shape parameter is less than 1. Moreover, because in traditional duration model settings, each firm only contributes only *one* observation, it is impossible to include year dummies directly into the duration models.

As mentioned earlier, the dynamic logistic model provides much more flexibility in specifying the function form of transition probability, compared with the traditional duration models, such as the duration model with Weilbull distribution. It is not necessary for us to specify the form of distribution beforehand. In particular, we are able to identify the possible non-monotonic duration dependence.[18] Studying the duration effect is further motivated by the assumption of an important reduced-form credit risk model. Jarrow, Lando and Turnbull (1997) assumed that credit rating transition follows a Markovian Chain, which means the transition probabilities only depend on current state, and the length of time being in the current state doesn't influence the migration probability.

For each observation, let $U_{i,t}$ ($D_{i,t}$) indicate whether a firm's rating was updated (downgraded) in month t. For instance, a firm that was downgraded in month 3 would have $D_{i,t}$=1, and $D_{i,t}$=0, otherwise. Further, we use vectors $Dummy_{i,t}$ and $Duration_{i,t}$ to represent the year dummy variables and forth-order polynomials respectively. We should note that the cut off points μ and the coefficients of covariates are estimated simultane-

[17]The survivor, density, and hazard function for the Weilbull distribution are as follows: $S(t) = \exp(-(\beta t)^{\alpha})$; $f(t) = \alpha\beta^{\alpha}t^{\alpha-1}\exp(-(\beta t)^{\alpha})$; $\theta(t) = \alpha\beta^{\alpha}t^{\alpha-1}$, where α is the shape parameter determining the duration effect.

[18]That is why we include forth-order polynomial in duration in our model.

ously. Consequently, the cutoff point μ will be the linear combination of year dummies, if we include dummies for all the time periods from year 1988 through 2001. Therefore, in order to identify the model, we have to restrict the year dummy for 1988 to zero, treated as a baseline. The main specification of the duration effect model is as follows:

$$Z_{i,t} = Intercept + \beta_1 Duration_{i,t} + \beta_2 Dummy_{i,t} + \epsilon_{i,t}, \tag{16}$$

where, as usual, $Z_{i,t}$ is the latent variable determining the indicator $U_{i,t}$ (or $D_{i,t}$).

4.1.1 Empirical Results

Table 5 reports the estimation results of the duration effect on the upgrade probabilities. All the four polynomial duration variables are statistically significant. This suggests that putting other things aside, duration affects the rating migration probabilities. Except for the dummy for year 2002, all the dummy variables are not significant. Further, there is no obvious trend characterizing the year dummies. The estimates of year dummies for the downgrade case (See Table 6) display similar features, except that dummies for year 1996 and 2000 are significant as well as for the year 2002. No trend is observed either. In addition, the third and forth polynomials of duration are not significant. So as we can see, duration influences upgrade and downgrade differently. In order to have a visual realization of the duration effect, we draw the estimated upgrade (downgrade) probabilities[19] against the durations. Figure 1 displays the predicted upgrade probability as a function of duration and year dummies. The inverted V-shape suggests that upgrade probability increases with the duration until reaching its highest around two and half years since entering the current credit rating, and then declines. This phenomena is strikingly consistent with the well documented empirical findings in the personal credit risk literature (see Gross and Souleles, (2002), and Jiang, (2003)). In particular,

[19]The estimated probabilities are calculated as follows: Prob = $1/(1+\exp(\beta \mathbf{X}_{i,T}))$, where $\mathbf{X}$ represents the vector of independent variables.

probability of delinquency increases from the time a credit card account is opened until about its two-year birthday and then decreases.

Figure 2 shows the predicted downgrade probability. It is interesting to notice that the shape of the two curves are very different. The roughly U-shaped curve indicates that downgrade decreases against duration, and only begins to increase with duration in a couple of years. One possible reason for the declining downgrade probability against the duration is the heterogeneity. Specifically, in terms of probability, firms whose ratings are downgraded very quickly are those with a high probability of downgrade, while those whose ratings are unchanged have a relatively low probability of downgrade. Thus, if we investigate the downgrade probability by putting all the firms together, we would observe the downgrade probability decreases over time. This effect is known as mover-stayer problem. (See Gourieroux, (2000), for more details.)

Another possible explanation, perhaps a more important reason, for the U-shaped downgrade probability curve could be the unwillingness of rating agencies to downgrade a firm drastically. They would rather downgrade a firm notch by notch until reaching the proper rating.[20] As a result, firms being downgraded will spend a relatively short time in the intermediate ratings. Put another way, the duration will be short. Consequently, short durations are associated with a large downgrade probability. Take the recent phenomenal bankruptcy of Enron Corporation for instance. On October 16, 2001 Moody's placed all the long term debts of Enron on review for possible downgrades. On October 29, 2001 Enron was downgraded to Baa2. On November 9, 2001 Moody's downgraded it to Baa3. Shortly after, on November 28, 2001 Moody's downgraded Enron's rating to B2. Once again very soon , on December 3rd, 2001 Enron's rating went down to Ca.[21]

[20]It is often stated that downgrades are more important for credit rating agencies to identify in order to protect their reputation. The author thanks Lynnette Purda for bringing this point to his attention.

[21]These materials were obtained from Moody's website, www.moodys.com.

However, when rating agencies upgrade a firm, if justified, there is no reason for them to hesitate. All related parties would be satisfied; managers are satisfied because of easier financing, and/or possibly higher option and stock returns; investors are satisfied because they are assured of the quality of their bond investments. Rating agencies will be satisfied because they will not lose their customers to the competitors[22].

4.1.2 Empirical Evidence of Rating Momentum

Although the anecdotal arguments at the end of the last section seem valid, some people may not think they are very convincing. In this section, we provide empirical evidence supporting our arguments.

If rating agencies are reluctant to downgrade a firm drastically, but to reach the proper rating through a series of downgrading, then a direct observation associated with this practise is that one downgrade would be followed by another downgrade. Put differently, downgrade will display momentum, which means a recent downgrade can predict the probability of the next downgrade . A couple of papers documented the existence of the downgrade rating momentum, but they could not find the evidence of upgrade rating momentum. Their findings provide some empirical evidences for our arguments. In this section, we take the advantages of the dynamic logistic model to investigate whether a rating change in the past year will influence the current rating migration probability.

First, we let $UP_{i,t}$ ($DOWN_{i,t}$) be an indicator function, which equals 1 if firm i was upgraded (downgraded) to the current credit rating in the last 12 months ranging from month t-11 to t-1, and 0 otherwise[23]. To investigate the momentum effect, we estimate

[22]Of course, some credit risk derivatives traders with particular positions would be unhappy.

[23]The exact algorithm determining the index value is as follows: We first let $UP_{i,t}$ be zero. Then, we

the following models:

$$Z_{i,t} = Intercept + \beta_1 Duration_{i,t} + \beta_2 Dummy_{i,t} + \beta_3 UP_{i,t} + \epsilon_{i,t}, \tag{17}$$

and

$$Z_{i,t} = Intercept + \beta_1 Duration_{i,t} + \beta_2 Dummy_{i,t} + \beta_3 DOWN_{i,t} + \epsilon_{i,t}, \tag{18}$$

The empirical results support our arguments. Table 7 reports the estimates for the upgrade case. The estimation results show that it does not change the coefficients and the associated Chi-squares significantly (Compare to Table 5), when we include the indicator UP in the duration model of upgrade. All the forth duration polynomials are still statistically significant, and UP is not significant at the 5% level. As for the downgrade, the results are the reverse. $DOWN$ is highly significant, with p-value less than 0.01% (See Table 8). Moreover, none of the forth-order polynomials in durations, $Duration_{i,t}$, is significant anymore, which suggests the duration effect on downgrade is mainly caused by rating momentum.

4.1.3 Duration Effect on Credit Rating

In this section, we estimate hazard rate models for credit ratings with only duration and dummies being the independent variables. Specifically, we let $Rating_{i,t}$ be the credit rating of firm i at time t. As usual, $Z_{i,t}$ is the latent variable determining credit ratings. We model the probability of obtaining higher credit ratings. Table 9 presents the estimation results. All the forth polynomials of durations are statistically significant. Further it is interesting to notice that out of the 14 year dummies, they decline almost monotonically with minor exception of years 1993 and 1998[24]. It is premature to conclude either the

compare the rating at time $t-1$ with ratings from time $t-2$ to $t-11$ consecutively. From time $t-2$ to $t-11$, if the credit rating is higher than that at time $t-1$, we conclude the computing loop, and end up with $UP_{i,t}$ being 0. If the credit rating is lower than that at time $t-1$, then we obtain the value of 1 for $UP_{i,t}$, because an upgrade has happened. If the rating did not change during the period from $t-1$ through $t-11$, $UP_{i,t}$ will take its initial value, namely zero.

[24]Recall that the pre-determined value of year 1988 dummy is zero.

credit quality of corporate America is declining over time, or credit rating is adopting more stringent rating policy. We will investigate these two competing explanations in greater depth in the next section.

Further, at the first thought, it seems very puzzling to notice that while the year dummies in the credit rating models are statistically significant, and monotonically decreasing, the year dummies in the rating downgrade model are not significant, and no trend is shown. If, as BLM argued, rating agencies have been adapting more and more stringent rating policy, then we should have observed more and more downgrades each year in our sample. Yet, actually this apparent puzzle is understandable. Since we have a relatively stable number of firms in our sample, and if each year a fixed amount of firms are downgraded, then we will observe that the overall credit quality of our sample firms are declining monotonically over years.

Duration is not a fundamental risk factor affecting firms' credit quality. The reason for significant duration effect is that duration captures the time varying effect of some fundamental risk factors. Further because we have not controlled any factors determining credit ratings, it is impossible to judge whether the declining trend of year dummies is due to declining credit quality or stricter rating agencies' policy.

4.2 Hazard Rate Models of Credit Ratings

In this section, I provide the estimation results using both hazard rate model and traditional model. Out of sample predicting power for these two models is compared based on how many credit ratings are correctly predicted by each model. Additional measures of predicting accuracy are also reported. Moreover, in this part we provide additional evidence supporting BLM's argument that rating agency are adopting more stringent rating policy. Table 10 reports the correlation matrix of the independent variables used in this paper.

4.2.1 Myth of "Myth or Reality?": Evidence of Stringent Rating Policy

In their notable paper, titled "The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality?", BLM argued that the increasingly exceeding number of downgrades over upgrades is due to more and more stringent rating policy by credit rating agencies, rather than due to the common belief of declining corporate credit quality. BLM used year dummies to proxy the changing credit rating policy. Their estimation results show clear declining year dummy trend, which suggests rating agencies are adapting more stringent rating policy. However, people may argue that this effect could be generated by their particular data structure. Specifically, each year BLM includes newly rated firms in their sample[25]. However, if each year those new issues are replete with firms of low credit quality whose credit ratings would be quickly downgraded, then we would observe the average credit rating become worse and worse. Put differently, the apparent time trend documented by BLM could be brought about by including the newly rated firms each year. Although BLM tried to control risk factors determining the credit rating, it is impossible to control all the factors, as admitted by BLM. Consequently, by introducing new issues every year, BLM is subject to the criticism of the validity of the estimations. In this section, we investigate this argument.

Table 11 presents parameter estimates for models with the whole sample from 1988 through 2001. As before, we model the probability of having higher credit ratings. The coefficient for all of the covariates have the correct signs in accordance with both theory and intuition. A negative sign means that variable has a negative effect on firms obtaining a higher rating. In an unreported estimation, we include market return in our

[25] In this paper, we only include the firms having a credit rating at the end of year 1988. That is why as time goes by, BLM has more cross-sectional units, while we have fewer firms.

model, and find the sign of market return is negative. Taken at face value, it means that other things being equal, a firm with a larger stock return will tend to receive a lower rating. However, when re-estimating the hazard rate model with only durations, excess market return and year dummies as covariates, we found that the sign of the coefficients for market return is positive, with estimates and Chi-square being 0.3695 and 37.968 respectively. Thus, possibly the correlation with other variables counts for the unexpected sign. In addition, it is interesting to notice that there still exists a duration effect even after we have controlled some notable risk factors.

The year dummies display a general downward trend over time, especially during the period from year 1989 to year 1997, which overlaps the time period of BLM samples. This decline in the year dummies is consistent with BLM's argument of application of increasingly more stringent standards over time in assigning ratings in terms of the BLM set of variables. Different to BLM, we have provided additional control of seasoned effect and nonparametric duration effect. BLM's argument survived our stricter examination. The statistical significance brought about significant economic importance as well (See BLM for an illustration). However, in Table 11, we can see that the downward trend was broken after year 1997. Curiously, in an unreported estimation, we re-ran the regression with un-truncated data, and the year dummies display an almost monotonic downward trend from the year 1989 to year 2001, although SSR and Interest coverage have wrong signs.

4.2.2 Forecasting Comparison

To investigate the relative predicting performance of the simple static logistic model and our hazard rate model, we divide our data into estimating sample and forecasting sample. Year 1996 is chosen as the cut off year[26]. When estimating hazard rate model, we

[26]Year 1996 is selected arbitrarily. To alleviate the concern of data mining, other cut off points are also tried, including years 1998, 1997, and 1995. They all yield the same conclusion.

use each year's covariates values to do the estimation. Table 12 presents the in-sample estimates for the hazard rate model. With regards to simple static logistic model, we follow BLM's practise, which is commonly used in the static method. Specifically, each factor's three year's average are used as covariate's value (See Table 13 for the estimations results). As we can see the estimates of these two models differ considerably, which will transfer into different predicating accuracy. After estimating these two models, we use the estimate coefficients and covariance matrix to predict the credit rating for the new sample. We compute the predicted probability of a firm falling in any of our 7 credit ratings. The rating with the highest predicted probability is the rating predicted by the models.

To assess the overall predicting accuracy, we calculate the percentage of credit ratings that were correctly predicted. Panel A of Table 14 reports the percentage of correct ratings for the BLM model and the hazard rate model using different size of training data. The year column represents the times used to cut the whole sample into estimation and prediction samples. As we can see in the Panel A, the hazard rate models outperform simple logistic models for all the different samples size choices. In Panel B of Table 14, we provide additional measures of predicting ability. They are based on the number of pairs of observations with different actual credit ratings, the number of concordant pairs, and the number of discordant pairs. A pair is defined as two observations with different credit ratings. A pair is said to be concordant (discordant) if the observation with the actual higher credit rating has the higher (lower) predicted event probability in that higher rating. If a pair of observations with different responses is neither concordant nor discordant, it is a tie. Enumeration of the total numbers of concordant and discordant pairs is carried out by categorizing the predicted probabilities into intervals of length 0.002 and accumulating the corresponding frequencies of observations. Let N be the sum of observation frequencies in the data. Suppose there is a total of t pairs with different responses, n_c of them are concordant, n_d of them are discordant, and $t - n_c - n_d$ of them are tied. SAS computes the following four measures of rank correlation for assessing the predictive ability of a model:

$$\begin{array}{l} c = (n_c + 0.5(t - n_c - n_d))/t \\ \text{Somers}'\text{D} = (n_c - n_d)/t \\ \text{Gamma} = (n_c - n_d)/(n_c + n_d) \\ \text{Tau} - \text{a} = (n_c - n_d)/(0.5N(N-1)). \end{array}$$

(See *SAS User Manual* for more details.) As we can see in Panel B, all the measures suggest that hazard rate model generates superior forecasting accuracy to the simple BLM models.[27]

5 Conclusion

This paper develops a hazard rate model for predicting credit rating and credit rating changes. The hazard rate model is theoretically more reasonable than the simple single period logistic type of model used heavily in previous researches on credit rating. The reason is that hazard rate model explicitly takes the time varying effect of both credit rating and covariates into consideration. It is able to utilize much more information than static model does. Avoiding the problem of arbitrarily choosing observation time, and averaging covariates values of arbitrarily chosen time periods, hazard rate model is immune to these selection biases. Yet hazard rate model with time varying covariates is very difficult to estimate. Mathematically, we show that we can use normal logistic method to estimate the time varying hazard rate model, which greatly simplifies its application.

We first study the duration effect and momentum effect on credit rating downgrade and upgrade. We confirmed previous findings that duration and momentum have an effect

[27] Hazard rate model has already been penalized by the more stringent rating policy. If we were able to control this effect, the relative performance of hazard rate would be even better.

on the probability of credit rating change. Taking advantage of the flexibility of hazard rate model, we solve the conflicting finding of previous studies. Specifically, duration has non-monotonic effect on the probability of credit rating changes. Further, for the first time, we documented that the duration effect on downgrade probability was mainly brought about by the momentum effect of downgrade.

We also empirically compared the forecasting ability of hazard rate model and simple static logistic model. All the predictability measures indicate that hazard rate model has superior forecasting power as opposed to the traditional models.

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Table 1: Firm-Month Observations of Credit Rating (frequency)

Year	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**C**	**Default**	**Total**
1989	589	2173	4591	3147	2340	3338	0	469	13	16647
1990	556	2083	4230	3203	1964	2464	453	42	10	14995
1991	525	1876	4060	3206	1763	1857	448	110	6	13845
1992	494	1796	4059	3082	1722	1532	377	133	5	13195
1993	452	1711	4085	3108	1760	1315	193	49	3	12673
1994	429	1648	3918	3170	1676	1135	90	18	0	12084
1995	406	1562	3868	3073	1482	984	91	2	6	11468
1996	415	1465	3793	2897	1442	872	79	1	0	10964
1997	403	1418	3715	2928	1301	791	70	7	3	10633
1998	360	1331	3550	2914	1152	581	36	6	1	9930
1999	306	1259	3328	2878	1051	517	14	0	7	9353
2000	224	1014	3116	2804	989	519	28	3	5	8697
2001	188	740	2882	2669	935	425	60	7	15	7906
2002	145	480	2115	2214	785	320	62	3	9	6124

This table presents the frequency of each credit rating in each year. It is based on the monthly observations of 1508 firms which had credit ratings at the end of year 1988. We track the complete rating history for each of the firms. If a firm's rating is withdrawn, we delete that firm from our sample from the month of withdrawal. If a firm defaults, we leave it out of our sample from the month immediately next to the default month. In total, we have 158514 monthly credit rating observations for 1508 firms covering the 14 years from 1989 through 2002.

Table 2: Firm-Month Observations of Credit Rating (percentage)

Year	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**C**	**Default**	**Total**
1989	3.54	13.04	27.56	18.89	14.05	20.04	0.00	2.82	0.08	99.94
1990	3.71	13.88	28.19	21.35	13.09	16.42	3.02	0.28	0.07	99.94
1991	3.79	13.54	29.31	23.15	12.73	13.41	3.23	0.79	0.04	99.95
1992	3.74	13.61	30.75	23.35	13.05	11.61	2.86	1.01	0.04	99.98
1993	3.57	13.5	32.23	24.52	13.88	10.37	1.52	0.39	0.02	99.98
1994	3.55	13.64	32.42	26.23	13.87	9.39	0.74	0.15	0.00	99.99
1995	3.54	13.61	33.71	26.78	12.92	8.58	0.79	0.02	0.05	99.95
1996	3.79	13.36	34.6	26.42	13.15	7.95	0.72	0.01	0.00	100
1997	3.79	13.33	34.93	27.53	12.23	7.44	0.66	0.07	0.03	99.98
1998	3.63	13.4	35.75	29.34	11.6	5.85	0.36	0.06	0.01	99.99
1999	3.27	13.45	35.56	30.75	11.23	5.52	0.15	0.00	0.07	99.93
2000	2.57	11.65	35.81	32.22	11.37	5.96	0.32	0.03	0.06	99.93
2001	2.37	9.34	36.38	33.7	11.8	5.37	0.76	0.09	0.19	99.81
2002	2.36	7.83	34.49	36.1	12.8	5.22	1.01	0.05	0.15	99.86

This table gives the percentage breakdown of credit ratings for each year. The table is based on the monthly observations of 1508 firms which had credit rating at the end of year 1988. We track the complete rating history for each of the firms. If a firm's rating is withdrawn, we delete that firm from our sample from the month of withdrawal. If a firm defaults, we leave it out of our sample from the month immediately next to the default month. In total we have 158514 monthly credit rating observations for 1508 firms covering the 14 years from 1989 through 2002.

Table 3: Summary Statistics of Credit Rating Durations

Rating	**Percentage**	**Mean**	**Std Dev**	**Maximum**
AAA	3.46	87.65	46.96	201
AA	12.97	80.02	47.04	201
A	32.3	74.76	49.13	201
BBB	25.96	59.37	45.85	201
BB	12.86	38.44	30.94	201
B	10.6	40.21	31.01	192
CCC	1.57	22.49	19.71	119
CC	0.24	11.94	15.28	190
Default	0.05	16.84	28.31	180

This table provides the descriptive statistics for the duration, namely how many months a firm has stayed in a specific rating class. The statistics are calculated using the monthly observations ranging from 1988 to 2002. The minimum duration for each credit rating is 1, because once a credit rating change occurred, the duration accumulation for the current rating begins with 1.

Table 4: Summary Statistics of Covariates

Variable	Mean	Median	Std.	Maximum	Minimum
Market return	-0.019	-0.009	0.349	0.987	-1.082
ssr	0.095	0.051	0.128	0.842	0.006
beta	0.912	0.850	0.989	4.117	-1.557
Interests coverage	5.951	4.152	6.985	49.03	-2.475
Total debt leverage	0.662	0.644	0.175	1.457	0.29
LT deb leverage	0.287	0.273	0.162	0.908	0.005
Market value	7.278	7.363	1.855	12.64	-3.194
Return variance	0.087	0.074	0.048	0.291	0.029
Operating margin	0.171	0.148	0.112	0.547	-0.043

Table 4 reports summary statistics for the independent variables used to explain and predict credit ratings. We track the history for a sample of 1508 firms, which had credit ratings at the end of year 1988. The sample period is from 1989 to 2001. Each firm contributes multiple firm-year observations. A firm is deleted from the sample when its rating is withdrawn or it goes into default. In total, there are 8430 observations having values for all the independent variables listed above, based on which summary statistics are calculated. Following Shumway (2001), all variables are truncated at the 99th and 1st percentile, so the Minimum and Maximum quantities reported are actually those quantiles.

Table 5: Dynamic Logistic Model of Duration Effect on Upgrade Probability

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	***P*-value**
Intercept	-5.9296	0.3784	245.5692	<.0001
duration	0.0747	0.0144	27.1011	<.0001
duration2	-0.1747	0.0358	23.8791	<.0001
duration3	0.1279	0.0322	15.7492	<.0001
duration4	-0.0302	0.0094	10.3474	0.0013
dummy1989	-0.1531	0.3512	0.19	0.6629
dummy1990	-0.552	0.364	2.2995	0.1294
dummy1991	-0.4384	0.3675	1.4236	0.2328
dummy1992	0.1007	0.359	0.0787	0.7791
dummy1993	0.3446	0.3576	0.929	0.3351
dummy1994	-0.1742	0.3731	0.218	0.6406
dummy1995	-0.1159	0.3737	0.0962	0.7565
dummy1996	-0.0956	0.3757	0.0648	0.7991
dummy1997	0.1134	0.371	0.0934	0.7599
dummy1998	0.15	0.3729	0.1619	0.6874
dummy1999	-0.227	0.3896	0.3396	0.56
dummy2000	-0.3394	0.3982	0.7264	0.394
dummy2001	-0.6246	0.4227	2.1836	0.1395
dummy2002	-1.0597	0.4917	4.6455	0.0311

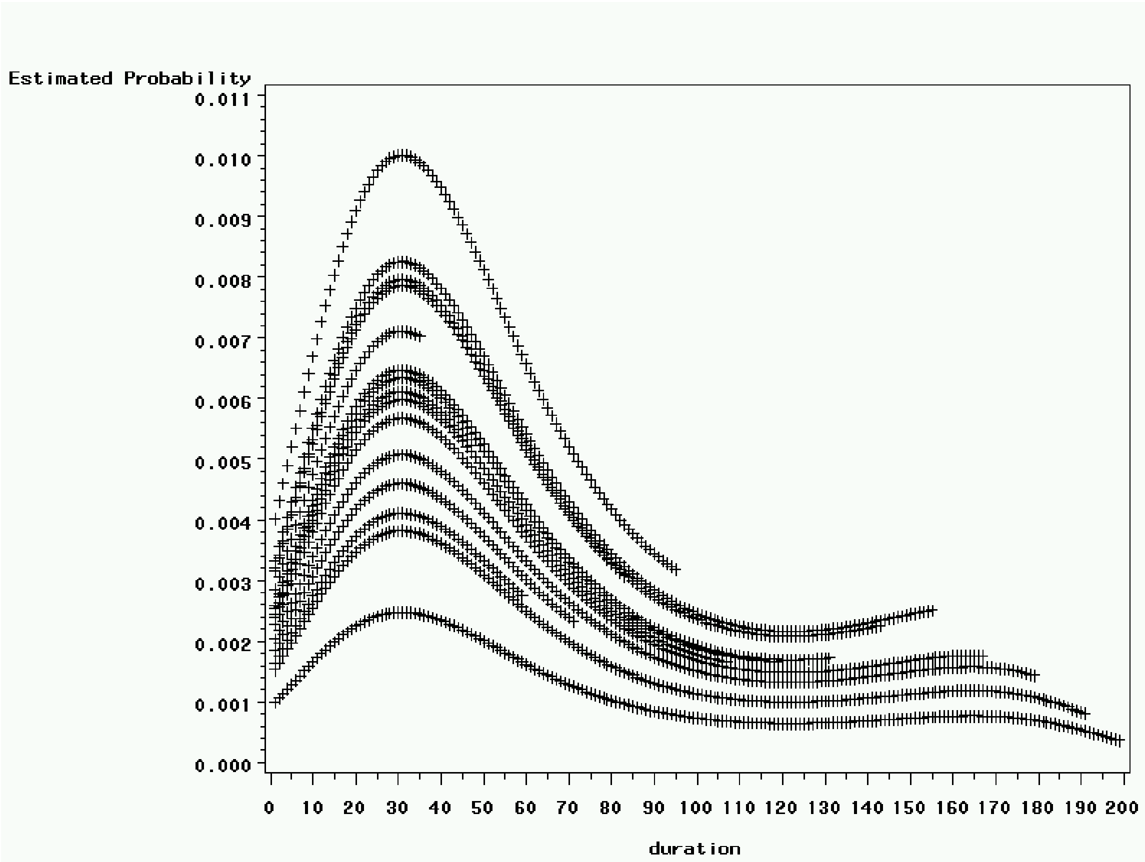
These estimates are for the dynamic logistic model of duration effect on credit rating upgrade using the monthly rating data from the beginning of 1989 through 2002. It models the probability of upgrade. We use an indicator function which equals 1 if a upgrade occurred by comparing one month's rating and that of the last month, and equals 0, otherwise. In order to prevent the coefficient of Duration2, Duration3, and Duration4 from being too small, we let Duration^n=Duration^{n-1}·Duration/100. The author thanks Yuze Jiang for this suggestion.

Table 6: Dynamic Logistic Model of Duration Effect on Downgrade Probability

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	***P*-value**
Intercept	-4.5582	0.3313	189.3483	<.0001
duration	-0.0284	0.00861	10.8832	0.001
duration2	0.0445	0.0207	4.612	0.0317
duration3	-0.0284	0.0173	2.6963	0.1006
duration4	0.00652	0.00463	1.9883	0.1585
dummy1989	0.1705	0.3293	0.268	0.6047
dummy1990	0.4866	0.328	2.2005	0.138
dummy1991	0.1833	0.3334	0.3025	0.5823
dummy1992	0.0354	0.3375	0.011	0.9165
dummy1993	-0.234	0.3443	0.462	0.4967
dummy1994	-0.5023	0.3532	2.0223	0.155
dummy1995	-0.3182	0.35	0.8262	0.3634
dummy1996	-0.8204	0.3699	4.9201	0.0265
dummy1997	-0.3237	0.3527	0.8423	0.3587
dummy1998	-0.3065	0.354	0.7495	0.3866
dummy1999	-0.0863	0.3486	0.0613	0.8044
dummy2000	0.6658	0.3347	3.9576	0.0467
dummy2001	0.5712	0.3371	2.8707	0.0902
dummy2002	0.7295	0.3401	4.6012	0.0319

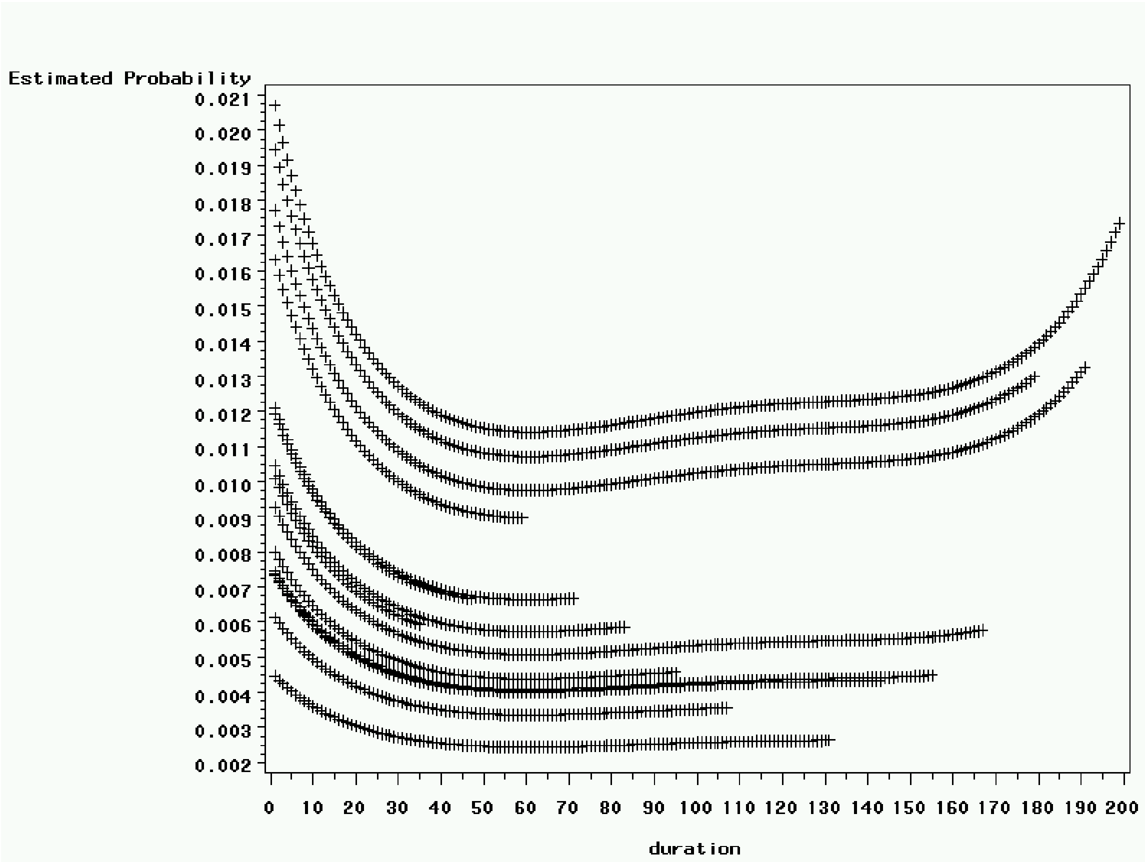
These estimates are for the dynamic logistic model of duration effect on credit rating downgrade using the monthly rating data from the beginning of 1989 through 2002. It models the probability of downgrade. We use an indicator function which equals 1 if a downgrade occurred by comparing one month's rating and that of the last month, and equals 0, otherwise. In order to prevent the coefficient of Duration2, Duration3, and Duration4 from being too small, we let Duration^n=Duration^{n-1}·Duration/100. The author thanks Yuze Jiang for this suggestion.

Figure 1: The Predicted Probability of Upgrade



This figure plots the upgrade probabilities against the duration in current rating. The upgrade probabilities were estimated from the dynamic logistic model with only forth-order polynomial in duration, and year dummies. Each curve represents hazard function for a different calender year. Each hazard function gives the average probability of a firm being upgraded, conditional on having been staying in the current rating.There is no regular order in these curves.

Figure 2: The Predicted Probability of Downgrade



This figure plots the downgrade probabilities against the duration in current rating. The downgrade probabilities were estimated from the dynamic logistic model with only forth-order polynomial in duration, and year dummies. Each curve represents hazard function for a different calender year. Each hazard function gives the average probability of a firm being downgraded, conditional on having been staying in the current rating. There is no regular order in these curves.

Table 7: Dynamic Logistic Model of Momentum Effect on Upgrade Probability

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	P**-value**
Intercept	-5.7598	0.3859	222.7927	<.0001
duration	0.0638	0.0152	17.648	<.0001
duration2	-0.1537	0.0368	17.39	<.0001
duration3	0.1123	0.0328	11.7392	0.0006
duration4	-0.0263	0.00948	7.7173	0.0055
UP	-0.4983	0.2703	3.3975	0.0653
dummy1989	-0.1422	0.3512	0.1639	0.6856
dummy1990	-0.5379	0.3641	2.1831	0.1395
dummy1991	-0.4283	0.3675	1.3585	0.2438
dummy1992	0.1117	0.359	0.0969	0.7556
dummy1993	0.356	0.3576	0.9913	0.3194
dummy1994	-0.1654	0.373	0.1965	0.6575
dummy1995	-0.1093	0.3737	0.0856	0.7698
dummy1996	-0.0859	0.3757	0.0522	0.8192
dummy1997	0.1279	0.371	0.1188	0.7303
dummy1998	0.1635	0.3729	0.1923	0.661
dummy1999	-0.2182	0.3895	0.3138	0.5753
dummy2000	-0.3403	0.3981	0.7306	0.3927
dummy2001	-0.6315	0.4227	2.2316	0.1352
dummy2002	-1.0747	0.4922	4.7673	0.029

These estimates are for the dynamic logistic model of momentum effect on credit rating, using the monthly rating data from the beginning of 1989 through 2002. It models the probability of upgrade. We let $UP_{i,t}$ be the indicator function which equals 1 if firm i was upgraded to the time $t-1$ rating from time $t-11$ to $t-1$, and 0 otherwise. In order to prevent the coefficient of Duration2, Duration3, and Duration4 from being toppo small, we let Duration^n=Duration$^{n-1}\cdot$Duration/100. The author thanks Yuze Jiang for this suggestion.

Table 8: Dynamic Logistic Model of Momentum Effect on Downgrade Probability

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	***P*-value**
duration	0.00117	0.0107	0.0121	0.9124
duration2	-0.00757	0.0236	0.1031	0.7481
duration3	0.00661	0.0189	0.1218	0.7271
duration4	-0.0014	0.00496	0.0795	0.7779
DOWN	0.6828	0.1308	27.2401	<.0001
dummy1989	0.1422	0.3294	0.1864	0.6659
dummy1990	0.4298	0.3282	1.7151	0.1903
dummy1991	0.1089	0.3337	0.1065	0.7441
dummy1992	-0.00499	0.3377	0.0002	0.9882
dummy1993	-0.2523	0.3445	0.5366	0.4638
dummy1994	-0.5096	0.3534	2.0803	0.1492
dummy1995	-0.3305	0.3502	0.8908	0.3453
dummy1996	-0.8347	0.37	5.09	0.0241
dummy1997	-0.3432	0.3529	0.9462	0.3307
dummy1998	-0.3338	0.3542	0.8877	0.3461
dummy1999	-0.1296	0.3489	0.138	0.7103
dummy2000	0.5963	0.3351	3.1671	0.0751
dummy2001	0.4956	0.3376	2.1558	0.142
dummy2002	0.6621	0.3403	3.7858	0.0517

These estimates are for the dynamic logistic model of momentum effect on credit rating, using the monthly rating data from the beginning of 1989 through 2002. It models the probability of downgrade. We let $DOWN_{i,t}$ be the indicator function which equals 1 if firm i was downgraded to the time $t-1$ rating from time $t-11$ to $t-1$, and 0 otherwise. In order to prevent the coefficient of Duration2, Duration3, and Duration4 from being too small, we let Duration^n=Duration^{n-1}·Duration/100. The author thanks Yuze Jiang for this suggestion.

Table 9: Dynamic Logistic Model of Duration Effect on Credit Ratings

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	***P*-value**
Intercept1	-4.3544	0.0875	2477.855	<.0001
Intercept2	-2.6128	0.0773	1142.276	<.0001
Intercept3	-0.9302	0.0747	155.008	<.0001
Intercept4	0.2892	0.0742	15.1952	<.0001
Intercept5	1.1899	0.0753	249.799	<.0001
Intercept6	3.2305	0.0927	1214.974	<.0001
Intercept7	5.1449	0.1692	924.1508	<.0001
Intercept8	6.6902	0.3398	387.6005	<.0001
duration	0.0117	0.00486	5.7505	0.0165
duration2	0.032	0.0118	7.2925	0.0069
duration3	-0.0349	0.0103	11.4664	0.0007
duration4	0.00968	0.00288	11.3005	0.0008
dummy1989	-0.0278	0.068	0.1672	0.6826
dummy1990	-0.1031	0.0707	2.1259	0.1448
dummy1991	-0.1809	0.0733	6.087	0.0136
dummy1992	-0.2137	0.0752	8.0714	0.0045
dummy1993	-0.211	0.0768	7.5486	0.006
dummy1994	-0.2637	0.078	11.4345	0.0007
dummy1995	-0.2826	0.0793	12.6978	0.0004
dummy1996	-0.3132	0.0805	15.1489	<.0001
dummy1997	-0.3219	0.0815	15.5947	<.0001
dummy1998	-0.2325	0.0835	7.7499	0.0054
dummy1999	-0.2835	0.0845	11.2486	0.0008
dummy2000	-0.3835	0.0872	19.3325	<.0001
dummy2001	-0.4569	0.0923	24.4896	<.0001

These estimates are for the dynamic logistic model of duration effect on credit rating, using the monthly rating data from the beginning of 1989 through 2002. It models the probability of having higher ratings. In order to prevent the coefficient of Duration2, Duration3, and Duration4 from being too small, we let Duration^n=Duration^{n-1}·Duration/100. The author thanks Yuze Jiang for this suggestion. The eight intercepts represent the cut-off points that cuts the domain of latent credit quality score into 8 different credit ratings and the state of default.

Table 10: Correlation Matrix of BLM covariates

Variables	Drtn	Drtn2	Drtn3	Drtn4	SSR	Beta	Mkt. rtn.	Mkt. value	LT levg.	Op. margin	Total levg.
Duration2	0.954										
Duration3	0.878	0.978									
Duration4	0.804	0.935	0.987								
SSR	-0.138	-0.092	-0.061	-0.040							
Beta	-0.136	-0.139	-0.136	-0.131	0.140						
Mkt. rtn	0.046	0.040	0.042	0.045	0.054	0.051					
Mkt. value	0.308	0.302	0.279	0.255	-0.400	-0.092	0.189				
LT levg.	-0.169	-0.153	-0.134	-0.117	0.218	0.026	-0.060	-0.419			
Op. margin	0.114	0.102	0.086	0.071	-0.186	-0.087	0.080	0.221	0.092		
Total levg.	-0.101	-0.071	-0.054	-0.044	0.284	0.045	-0.074	-0.249	0.536	-0.038	
Ints. covg.	0.173	0.166	0.154	0.141	-0.169	-0.030	0.083	0.374	-0.445	0.097	-0.397

Table 10 provides the correlation matrix for the BLM sets of covariates plus the excess market returns, which were calculated from 8430 observations. In the first row, we use Drtn to represent Duration, Drtn2 to represent Duration2, so on and so forth. The correlation could be problematic, because time series observations for each firm are not independent. An alternative method is to compute the mean for each variable and then compute the correlations coefficients.

Table 11: Hazard Rate Model Estimates for Credit Rating with BLM Covariates

Parameter	Coefficient	Std.Err.	Chi Sqr.	P-value
Intercept1	-10.0195	0.225	1982.576	<.0001
Intercept2	-7.5105	0.204	1355.336	<.0001
Intercept3	-4.8913	0.1921	648.5532	<.0001
Intercept4	-2.5137	0.1869	180.9645	<.0001
Intercept5	-0.4289	0.1897	5.1136	0.0237
Intercept6	3.8194	0.2383	256.972	<.0001
Intercept7	6.2526	0.3017	429.3832	<.0001
Intercept8	6.9182	0.3269	447.7586	<.0001
duration	-0.00417	0.007	0.3557	0.5509
duration2	0.0525	0.0168	9.7703	0.0018
duration3	-0.0488	0.0145	11.3896	0.0007
duration4	0.0133	0.00402	10.8801	0.001
SSR	-5.9524	0.2413	608.7195	<.0001
Beta	-0.2313	0.0228	103.211	<.0001
Market Value	0.8345	0.0175	2281.997	<.0001
LT debt leverage	-3.9618	0.1747	514.0324	<.0001
Operating margin	2.8592	0.1877	231.9734	<.0001
Total debt leverage	-1.1514	0.1503	58.6858	<.0001
Interests coverage	0.0457	0.00384	141.892	<.0001
dummy1989	-0.1871	0.0957	3.8213	0.0506
dummy1990	0.083	0.1003	0.6854	0.4077
dummy1991	-0.2682	0.104	6.6566	0.0099
dummy1992	-0.4994	0.1065	21.9952	<.0001
dummy1993	-0.7431	0.1089	46.5899	<.0001
dummy1994	-0.8166	0.1089	56.2197	<.0001
dummy1995	-1.033	0.1111	86.3983	<.0001
dummy1996	-1.1961	0.1124	113.163	<.0001
dummy1997	-1.4336	0.1146	156.5988	<.0001
dummy1998	-1.0089	0.1176	73.6315	<.0001
dummy1999	-0.9673	0.1207	64.183	<.0001
dummy2000	-0.9485	0.1271	55.6553	<.0001
dummy2001	-1.3105	0.1299	101.7385	<.0001

These estimates are for the dynamic logistic model using a data set of 8430 observations from 1989 through 2001, with R-Square, Likelihood Ratio and -2 Log L being 0.6922, 9309 and 19152 respectively. It models the probability of having higher ratings. SSR is the sum of the square of residual estimated from the market model of stock market returns.

Table 12: Hazard Method Estimates for Data 1988-1996

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	***P*-value**
Intercept1	-9.5405	0.2642	1303.768	<.0001
Intercept2	-7.0872	0.242	857.618	<.0001
Intercept3	-4.6195	0.2293	405.7643	<.0001
Intercept4	-2.4373	0.2235	118.8823	<.0001
Intercept5	-0.3537	0.2264	2.4393	0.1183
Intercept6	4.3407	0.2916	221.5756	<.0001
duration	-0.00897	0.0124	0.5235	0.4694
duration2	0.1074	0.0393	7.4567	0.0063
duration3	-0.1479	0.046	10.3228	0.0013
duration4	0.0579	0.0177	10.7551	0.001
SSR	-8.2468	0.3571	533.3225	<.0001
Beta	-0.1531	0.0255	35.9537	<.0001
Market value	0.777	0.0206	1422.49	<.0001
LT debt leverage	-4.248	0.2125	399.4558	<.0001
Operating margin	3.1958	0.2205	209.9884	<.0001
Total Debt leverage	-1.4307	0.1809	62.5754	<.0001
Interest coverage	0.0423	0.0047	81.1283	<.0001

Hazard rate model is estimated with data from 1988 to 1996, with each year's independent value being the covariates. In total, we have 6038 firm year observations. Year dummies are excluded, because it is impossible to forecast with year dummy variables. Further, credit rating CCC, C, and Default are merged, because in year 1996,we don't have firms with both rating C or Default and covariate values.

Table 13: Simple Logistic Method Estimates for year 1996

Parameter	**Coefficient**	**Std.Err.**	**Chi Sqr.**	***P*-value**
Intercept1	-8.3121	1.1033	56.7553	<.0001
Intercept2	-5.6328	1.0358	29.5707	<.0001
Intercept3	-2.692	1.0022	7.2155	0.0072
Intercept4	0.0939	1.002	0.0088	0.9254
Intercept5	2.9014	1.0422	7.7505	0.0054
Intercept6	9.1878	1.4104	42.4361	<.0001
duration	-0.2879	0.0788	13.3407	0.0003
duration2	0.9375	0.2438	14.7885	0.0001
duration3	-1.07	0.2779	14.8231	0.0001
duration4	0.4041	0.1044	14.995	0.0001
SSR	-10.2157	1.5981	40.8637	<.0001
Beta	-0.5736	0.1196	23.0106	<.0001
Market value	0.7641	0.0716	114.0167	<.0001
LT debt leverage	-2.7404	0.374	53.6916	<.0001
Operating margin	4.6748	0.7639	37.4496	<.0001
Total Debt Leverage	-0.942	0.6249	2.2729	0.1317
Interest coverage	0.0377	0.0139	7.4077	0.0065

The simple logistic model is estimated for the year 1996. Following BLM, three year average are used to determine the value of the model covariates. The number of observations is 617. Year dummies are excluded, because it is impossible to forecast with year dummy variables. Further, credit rating CCC, C, and Default are merged, because in year 1996, we don't have firms with both rating C or Default and covariates values.

Table 14: Comparison of Forecasting Accuracy of BLM and Hazard Rate Model

Year	BLM	Hazard
1995	48.30%	49.17%
1996	48.66%	49.83%
1997	50.00%	51.08%
1998	51.09%	51.19%

Panel A:Percentage of Correct Predicting

Model	Concordant	Discordant	Tied	Somers' D	Gamma	Tau-a	c	R^2
BLM	76.7%	11.9%	11.3%	0.648	0.731	0.490	0.824	0.411
Hazard	80.1%	11.9%	7.90%	0.682	0.740	0.515	0.841	0.551
Pairs:	3322590							

Panel B: Association of Predicted Probabilities and Actual Ratings for Year 1995