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## Modelling the Persistence of Credit Ratings When Firms Face Financial Constraints, Recessions and Credit Crunches.

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# Modeling the persistence of credit ratings when firms face financial constraints, recessions and credit crunches

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**Abstract**

Making accurate predictions of corporate credit ratings is a crucial issue to both investors and rating agencies. Recent events have drawn attention to ratings agencies methods. In this paper we investigate the determinants of credit ratings as a function of financial variables; we then consider whether there is persistence in ratings for different types of firms in recessions and credit crunches. Using data on US firms rated by Fitch we find substantial evidence of persistence in ratings, and great improvements in prediction as a result. Credit ratings vary for firms facing binding/non-binding financing constraints but do not vary for in recessions/credit crunches and other periods therefore agencies rate "through the cycle".

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# I Introduction

Recent turmoil in the financial markets has focused attention on the rating agencies and the process by which they assign ratings to firms and their financial obligations. Ratings provided by credit risk agencies are a long-term assessment of the issuer's ability to service debt in a timely manner and are intended to be comparable across industry groups and countries.[1] Frequent changes in ratings are undesirable from the point of view of investors and firms, whose financing options and costs may be affected by ratings through regulation, covenant provisions on loans or bonds, and reduction of ratings in other markets e.g. commercial paper markets (see Kisgen (2006)). Rating agencies claim that they rate "through the cycle", implying that their ratings should be accurate but also stable over time and independent of the state of the business cycle (Cantor and Mann (2007)), with ratings conditional on underlying financial and business characteristics (c.f Amato and Furfine (2004)). They have strong incentives to achieve accuracy and stability because potentially procyclicality could contribute to market volatility. The longevity and success of the rating agencies suggest that the production of such risk assessments has been greatly used by investors.[2] Cantor and Mann (2003) argue that rating reversals are rare even at a five-year horizon. Yet, the large number of rating downgrades during the US corporate credit meltdown in 2001–2002 cast some doubts on the role, influence and dynamic properties of credit ratings. In this paper we analyze the determinants of ratings and how persistent they are after allowing

[1] Three rating agencies, Moody's, Standard and Poor's and Fitch, have a long history and dominate the US credit rating industry. The first two agencies have a policy of rating all taxable corporate bonds publicly issued in the US, while Fitch rate issuers on request. The bond ratings provided by these agencies are generally comparable and the rating scales are found to be uniform. The ratings assigned from these agencies are expressed in letter form, ranging from AAA (Aaa for Moody's), the highest, to C, the lowest. The division of the rating scale into these buckets is intended to divide a continuum of risk into discrete risk classes based on an assessment of the capacity of the debt issuer to meet its ongoing financial obligations. The highest rating, AAA, indicates an extremely strong capacity to pay interest and repay principal, while the lowest rating, C, indicates a serious vulnerability to default on payment. Debt rated from AAA to BBB is considered "investment" grade, while debt rated at BB and below is considered "speculative" grade.

[2] Rating agencies have standardized procedures for the preparation of ratings and the conduct of rating committees for the benfit of investors. At the beginning of the rating process agencies gather information sufficient to evaluate the risk to investors who own or buy a given security. This is done by employing a primary analyst who is responsible for the formulation of the rating opinion. Fitch's analysis is based on information received from all available sources, (see Fitch (2006b)). This includes relevant publicly available information on the issuer, such as company financial and operational statements, reports filed with regulatory agencies and other economic and industry reports. As well as incorporating public information, Fitch uses private/confidential information directly provided by the rated issuer. The gathered information and the proposed rating is then reviewed in a committee which develops a conclusion on the appropriate rating. The committee make use of both qualitative and quantitative analyses that most appropriately reflects the current situation and prospective performance. If there are no unresolved issues, a rating is assigned and the outcome of the committee is communicated to the marketplace and market participants. These ratings are monitored on an ongoing basis to determine whether they should be changed. Any changes – whether an affirmation, downgrade, or upgrade – become publicly available.

for firm-specific characteristics and financial constraints. We also consider procyclicality in ratings by comparing ratings for recessions and credit crunches and other periods. Our results demonstrate that there is strong persistence and little evidence of procyclicality. Unlike most other papers in the literature, with the exception of Amato and Furfine (2004), we use our models to predict ratings in- and out-of-sample and find good predictive ability based on statistical comparison of predictions and outcomes.

Analysis of ratings has a long pedigree (see Pogue and Soldofski (1969); Pinches and Mingo (1973); Kaplan and Urwitz (1979) and Kao and Wu (1990)) and has sought to explain the relationship between ratings and financial or business risks. One particular focus has been the examination of ratings behavior over time by considering increased volatility in corporate creditworthiness during the mid-1980s and early 1990s and the accompanied downward momentum. Recent examples include Blume et al. (1998) (BLM) and Amato and Furfine (2004) (AF). The first paper, documents that credit ratings have, on average, become worse through time - so that a firm initially rated as AA on the basis of its risk characteristics has been rated lower than AA subsequently. Blume et al. (1998) therefore provides evidence that the standards of ratings agencies have become more stringent over time. By contrast, Amato and Furfine (2004) do not identify a secular change in rating standards. In some specifications, they even find that the standards of ratings agencies have become more lenient over time. Their results imply that ratings changes are driven by cyclical changes to business and financial risks, and not to cycle-related changes to rating standards. The debate on the cyclicality in ratings is still ongoing.

Other authors, including Kisgen (2006, 2008) and Faulkender and Petersen (2006), have considered the effect of ratings or proximity to rating change on the capital structure of the firm. In these papers they do not seek to explain the ratings themselves, but indicate the importance of rating levels and changes to ratings for financial decisions of the firm. A downgrade can trigger covenants, breach regulatory limits forcing sales of bonds, increase disclosure requirements and increase the cost of funds in bond, commercial paper, and swap markets, since a rating downgrade is used as an information signal on factors unobservable to investors. Financial officers in corporations therefore make adjustments to financial composition to avoid the costs of rating downgrades or make upgrades more likely. These conclusions point to the fact that stability and accuracy of ratings have very real effects on firms, which underlines the importance of determining whether the ratings reflect full firm-specific information through the cycle.

In this paper we offer methodological extensions to examine the persistence in the rating process, adding to the literature in four ways. First, we allow for persistence in credit ratings. Previous studies that analyze the determinants of credit ratings in relation to business and financial risks (BLM (1998), AF (2004)) use static ordered probit models that do not allow for the influence of previous rating history on the current rating. There is, however, clear evidence of persistence in ratings, and the rating agencies aim to rate through the cycle, so our model allows for persistence in the observed outcomes due to state dependence (initial and previous states).

Second, we determine whether the agencies' approach to rating assignment systematically accounts for the firm-specific risks associated with the financial and business structure. We also explore whether the determinants of ratings allows for firm-level heterogeneity. BLM find in their paper that accounting ratios are more informative for larger firms compared to smaller firms, noting the implications for regulatory agencies. In addition, Pagratis and Stringa (2009) find that financial variables tend to have a more pronounced effect on subinvestment grade bank ratings compared to investment grade bank ratings. We argue that it is equally important to consider the binary classification "financially constrained" versus "not financially constrained" since this characteristic dramatically alters perceptions of creditworthiness, access to credit and defaults. Exploiting firm-specific heterogeneity in the context of credit ratings appears to be important for both ratings agencies and investors. The argument is that ratings changes (and especially downgrades) can have a disproportionate impact on an issuer's cost and availability of capital, the price of bonds, and occasionally, equity (c.f. Cantor and Mann (2003) and Kisgen (2006)) Therefore, it is of particular importance to disentangle the impact of financial variables for firms being credit constrained.

Third, we also look at firms in downturns/crunches to assess whether ratings vary in a systematic way between downturns and credit crunches and other periods. For firms with speculative-grade ratings the impact of poorer financial health during a recession is likely to have a greater impact on ratings than for investment grade firms. Kisgen (2006, 2008) details many costs that are likely to fall disproportionately on firms transiting the investment-grade/speculative-grade boundary; and in addition we argue that more transitions are likely in recessions and credit crunches. By looking at recessions and credit crunches we address the issue of procyclicality in ratings and its impact on different types of firms. Procyclicality of ratings is important because it can exacerbate a distressed company's difficulties and ultimately its ability to access credit. There is strong evidence in the literature (see Johnson (2003)) that under these conditions and for firms classified as constrained, there will be greater sensitivity to business and financial risks.

Finally, we evaluate the proportion of correct predictions from each dynamic model to directly assess the predictive ability of ratings, correcting for the effect of persistence that upwardly biases the evaluation, using Merton's correct prediction statistic (Merton (1981)). This extends earlier models by, for example, Amato and Furfine (2004) who evaluate the relative performance of the estimated models in terms of an informal goodness of fit indicator (by comparing the predicted ratings to the observed ones). Our test will give us a better indicator of the "true" predictive ability of rating models.

The paper is organized as follows. Section two discusses the methodology, and Section three presents the data used in our empirical analysis. Section four reports the results and Section five gives the model predictions. In Section six we check for the robustness of our findings before drawing conclusions in Section seven.

# II Methodology

Before we can properly evaluate the ratings procedure undertaken by the ratings agencies, it is important to take into account the characteristics of ratings and the issuing firms that are being rated. In this section we explain how we modify the existing methodologies to account for these characteristics. First, we present the ordered probit analysis employed so far in the literature. Second, we take note of the persistence in ratings and ensure that our model giving the probability that an issuer will fall into a particular rating category accounts for the information in the past history of ratings. Third, because firms have heterogeneous responses to information variables indicating creditworthiness, these will be a critical factor in determining an issuer's rating. We therefore allow for categorizations that distinguish between firms that are likely to be financially constrained and those that are not. We expect issuers to respond differently to measures of business and financial risk according to whether they are financially constrained or unconstrained. Fourth, we allow for the rating agencies' practice of rating "through the cycle" by looking for persistence in the ratings and distinguish between periods of credit crunch/recession versus other times when credit is not restricted and the economy is healthy. Finally, we explain how the evaluation of ratings using tests of predictive performance can quantify the ability of our model to predict ratings using the types of information used by ratings agencies.

## A. Baseline model

We begin our analysis with the static framework which serves as a starting point and will be used for comparison purposes. Credit ratings can be viewed as resulting from a continuous, unobserved creditworthiness index. Each rating corresponds to a specific range of the creditworthiness index, with higher ratings corresponding to higher creditworthiness values. Therefore, credit ratings are discrete-valued indicators and have an ordinal ranking. Typically, credit ratings are modeled through an ordered probit methodology.

The model description follows Maddala (1983). We define the categorical variable $y =$ 1, 2,.., 5 according to the actual rating assigned to each firm. Without loss of generality we record AAA-AA as 1, A as 2 ... B-CC as 5. This ordinal response can be modeled through a static ordered probit model of the following type:

$$y_{it}^* = X_{it}\beta + \alpha_i + \epsilon_{it} \tag{1}$$

where $y_{it}^*$ is an unobserved index of credit quality, $i$= 1,..., $N$ refers to firms and $t$= 1,..., $T$ refers to time periods, $X_{it}$ denotes a set of explanatory variables for firm $i$ and year and $\beta$ is a $k$x1 vector of unknown parameters to be estimated. $\alpha_i$ is a firm-specific and time invariant component and $\epsilon_{it}$ is the disturbance term which is assumed to be normally distributed. Both $\alpha_i$ and $\epsilon_{it}$ are scalars. To control for cyclical factors originating from the business cycle we include time dummies in our regressions for each year. We also include industry dummy variables to control for the unique influence of regulations within industrial groups. In our analysis we consider a pooled probit which does not require strong exogeneity assumptions, however, our model is potentially subject to a critique that this method fails to consider unobserved heterogeneity across firms. Since our panel includes repeated estimates from each firm it is possible that the residuals from the above model are correlated across time for the same firm within our panel. To address this issue we correct for unobserved heterogeneity in the robustness section of the paper. Specifically, we allow the residuals to have the following "random effects" structure: $\epsilon_{it} = u_i + v_{it}$, where $u_i$ are independent across firms and $v_{it}$ are independent across all observations.

In our data $y_{it}^*$ is not observed, thus we use credit ratings assigned to firms, which can take $M$ values for the observed variable, $y_{it}$, that are assumed to be related to the latent variable $y_{it}^*$ through the following observability criterion:

$$y_{it} = m \text{ if } a_{m-1} < y_{it}^* \leq a_m \text{ for } m = 1, \dots, M \tag{2}$$

for a set of parameters $\alpha_0$ to $\alpha_M$, where $\alpha_0 < \alpha_1 < ... < \alpha_M$, $\alpha_0 = -\infty$ and $\alpha_M = \infty$. Assuming a standard Normal distribution for $\epsilon_{it}$ the conditional probabilities can be derived as:

$$Pr(y_{it} = m) = \Phi(\alpha_m - X_{it}\beta - \alpha_i) - \Phi(\alpha_{m-1} - X_{it}\beta - \alpha_i) \tag{3}$$

where $\Phi(.)$ is the standard Normal distribution function. We can evaluate the above probabilities for any combination of parameters $\alpha$, $\beta$. To derive the likelihood function for the ordered probit model, we can define an indicator variable $z_{im}$=1$(y_{it} = m)$ for $m$= 1,..., $M$. Then the log-likelihood function which can be used to estimate the ML coefficients is given by:

$$lnL = \sum_{i=1}^{n} \sum_{m=1}^{M} = z_{im} ln[\Phi(\alpha_m - X_{it}\beta - \alpha_i) - \Phi(\alpha_{m-1} - X_{it}\beta - \alpha_i)] \tag{4}$$

## B. Persistence and the dynamic ordered probit framework

It has been argued that agencies are sometimes slow to respond to new information (see Odders-White and Ready (2006)). This occurs primarily for reasons inherent in the rating setting process within the credit ratings industry. Several studies note that rating changes tend to exhibit serial correlation (see Carty and Fons (1994) and Gonzalez et al. (2004)). In fact, rating agencies claim that they "rate through the cycle" implying that credit ratings should be stable over time.[3] Altman and Kao (2004) document serial autocorrelation in ratings below investment grade suggesting that a downgrade is more likely to be followed by a subsequent downgrade than by an upgrade. Finally, Pagratis and Stringa (2009) show that bank ratings tend to be sticky and therefore persistence appears to be very important in predicting bank ratings.

One basic premise of this paper is that modeling credit ratings should take into account the persistent nature of ratings. We estimate a reduced-form model including previous rating states in order to capture state dependence and the model can be interpreted as a first-order Markov process. The general dynamic specification that we estimate follows the literature (see Wooldridge (2005), Contoyannis et al. (2004) and Greene and Hemsher (2008))[4] and can be written as:

$$y^*_{it} = X_{it}\beta + y_{it-1}\gamma + y_{i0}\delta + \alpha_i + \epsilon_{it} \tag{5}$$

Let $X_{it}$ be a 1x$k$ vector of explanatory variables and $\beta$ is a $k$x1 parameter vector. $y_{it-1}$ is a vector of indicators for the firm's rating in the previous year and $\gamma$ are parameters to be estimated. $y_{i0}$ is the initial period value, $\alpha_i$ is a firm-specific and time invariant component and $\epsilon_{it}$ is the disturbance term. We observe an indicator of the category in which the latent indicator falls. Assuming a normally distributed error structure with zero mean and unit variance the probability of observing the particular category of rating $m$ reported by firm $i$ at time $t$ is given by:

[3] Long-term generally means at least one business cycle. Ratings agencies, however, claim that they are using an indefinite time horizon.

[4] The general framework of dynamic ordered probit models is presented in Wooldridge (2005) p. 48 and an application of the dynamic ordered probit model to health indicators is shown in Contoyannis et al. (2004).

$$P_{itm} = Pr(y_{it} = m) = \Phi(\alpha_m - X_{it}\beta - y_{it-1}\gamma - y_{i0}\delta - \alpha_i) - \Phi(\alpha_{m-1} - X_{it}\beta - y_{it-1}\gamma - y_{i0}\delta - \alpha_i) \quad (6)$$

Estimation of the ordered probit model with persistence can be performed by maximizing the log-likelihood function using standard numerical techniques. Assuming that the density of the individual effect is $N(0, \sigma_a^2)$, the log-likelihood function is:

$$lnL = \sum_{i=1}^{n}\{ln \int_{-\infty}^{+\infty} \prod_{t=1}^{T}(P_{itm})[(1/\sqrt{2\pi\sigma_a^2})exp(-a^2/2\sigma_a^2)]da\} \quad (7)$$

Evaluation of the above expression requires numerical integration which can be calculated by adaptive Gauss-Hermite quadrature. Since we estimate a dynamic model we need to take account of the problem of initial conditions. Thus, we estimate the model allowing for state dependence and accounting for the initial conditions problem (Heckman (1981) and Wooldridge (2005)). We adopt the procedure suggested by Wooldridge (2005) to deal with the problem of initial conditions. This problem is due to the generic feature of the panel that firms (or individuals) inherit different unobserved and time-invariant characteristics which affect outcomes in every period. The ordered probit models are estimated using maximum likelihood estimators which are available in standard econometric software.

The main advantage of the dynamic ordered probit model compared to the static one is that it explicitly addresses the issue of persistence. Persistence is the casual link between the probability of obtaining a rating in year $t$ and past realizations of rating, which is typically tested by introducing lagged values of the dependent variable. In our context, previous rating status should improve predictive power compared to its static counterpart.

## C. Constrained/unconstrained firms

A large literature has considered the impact of financial constraints on investment in fixed capital, inventory investment, and employment and R&D activities (see Hubbard (1998) for a survey). In many cases the response of firms to indicators of creditworthiness is found to be dependent on whether firms are likely to be "financially constrained" or "not financially constrained"; however, the results can be influenced by the categorization process used to determining whether firms are financially "constrained" or "unconstrained" (see, e.g, Fazzari et al. (1988, 2000); Kaplan and Zingales (1997, 2000) and the discussion in Almeida and Campello (2007a,b) and Khurana et al. (2006)). The scholarly literature has not settled on a universally accepted strategy to identify financially "constrained" and "unconstrained" firms empirically, but the classification scheme can be critically important for the conclusions of these studies. Therefore, in this paper we use the widely used technique in empirical research that employs three different measures of financial constraints to ensure the robustness of our results, these are indebtedness, dividend payout ratio and size.

Size was employed as a criterion by Almeida and Campello (2007b) Bougheas et al. (2006) and is the key proxy for capital market access by manufacturing firms in because small firms are more vulnerable to capital market imperfections and thus more likely to be financially constrained. The dividend payout ratio, as measured by the ratio of total dividends to total assets, has been used by a number of studies (see for example Fazzari et al. (1988, 2000) and Almeida and Campello (2007b)) because it is argued that firms will refrain from distributing earnings if they expect to rely on these for real investment, and they will do so if they are financially constrained. Firms that are more indebted (based on the gearing ratio, defined as total debt over shareholders' equity) are more likely to pay a higher external finance premium on bonds since they have a greater probability of bankruptcy (Bougheas et al. (2006)), which can raise the cost of borrowing, and negatively affect the availability of credit. We report results using all three classification schemes. Firms in the top 25th percentile of the distribution of size and dividends are regarded as unconstrained and those in the bottom 25th percentile are classified as constrained. For indebtness we use leverage as sorting device and follow the reverse categorization. We also allow firms to transit between firm classes.[5]

We use indebtedness, dividend payout ratio and size to define a dummy vector consisting of three different binary variables reflecting financing constraints. This financial constraint dummy vector, $C_{it}$, is interacted with measures of business and financial risk to determine whether the rating probability assigned by the dynamic ordered probit model varies with this categorization:

$$y_{it}^* = X_{it}\beta_1 C_{it} + X_{it}\beta_2(1 - C_{it}) + y_{it-1}\gamma + y_{i0}\delta + \alpha_i + \epsilon_{it} \tag{8}$$

Here the dummy vector ($C_{it}$) is interacted with the vector of business and financial risk variables ($X_{it}$) in our baseline specification. It will be apparent from these models whether business and financial risk information is weighted differently for financially constrained versus unconstrained firms by the significance of the coefficients on the interacted term. From the ratings predictions we will be able to determine whether measures of predictive ability are noticeably different when we account for this characteristic of issuers.

[5] For this reason, our empirical analysis will focus on firm-years rather than simply firms. See Kaplan and Zingales (1997) for a similar approach.

## D. Ratings, recessions and credit crunches

Rating agencies have two broad objectives – accuracy and stability (see Cantor and Mann (2007)). The former refers to the correlation of ratings with subsequent credit loses, while the latter refers to the frequency and magnitude of rating changes. In order to achieve stability over time they assign ratings using a long-term perspective which takes into account one business cycle. Therefore, rating agencies desire ratings to be stable and not be driven in a cyclical manner by booms or recessions or by sharp reductions in the availability of credit. If ratings were procyclical, then they could potentially induce increasing market volatility and make the credit cycle more pronounced (see Cantor and Mann (2003)). AF (2004) test whether business cycle variables have a marginal effect on the rating assigned to a firm. They present an empirical model in which, in addition to business and financial risks and macroeconomic conditions, they distinguish secular and cyclical influences on ratings. They show that rating changes exhibit very little cyclicality even after controlling for many of the financial and economic determinants of ratings.

In our analysis we seek to determine whether periods of business cycle downturns and credit crunches are important for different types of firms. This is an important dimension to be explored since rating cyclicality can exacerbate a distressed company's difficulties and ultimately its ability to access credit. We approach this issue by specifying a time-period dummy variable to indicate that the US economy is in recession or credit crunch. The identification of downturns and upturns follows the Business Cycle Dating Committee of the National Bureau of Economic Research which determined that a trough in business activity occurred in the US economy in November 2001.[6] The trough marked the end of the recession that began in March 2001 and the beginning of an expansion. This was also referred to as a credit crunch - in which some firms were excluded from gaining access to credit - it lasted from 2001- 2002, and was closely associated with the recession of 2001 (Kwan (2002)). Therefore, in order to explore whether credit ratings move procyclicaly, we will interact a recession/crunch dummy with all measures of business and financial risk to determine whether the rating probability assigned by the dynamic ordered probit model varies with the cycle and credit conditions.

To explore the sensitivity of firms' ratings and procyclicality, we employ another set of dummy variables, where the dummy vector, $D_t$, takes the value 1 for the recession/credit crunch period, and 0 otherwise. We estimate the following model:

[6] Our approach is consistent with other studies that looked at the procyclicality of ratings (see Cantor and Mann (2003) and AF (2004)).

$$y^*_{it} = X_{it}\beta_1 C_{it} D_t + X_{it}\beta_2 C_{it}(1-D_t) + X_{it}\beta_3(1-C_{it})D_t + X_{it}\beta_4(1-C_{it})(1-D_t) + y_{it-1}\gamma + y_{i0}\delta + \alpha_i + \epsilon_{it} \quad (9)$$

The dummy vector ($D_t$) is interacted both with the vector of financial variables ($X_{it}$) in our baseline specification and the dummy vector of financing constraints ($C_{it}$) defined in the previous sub-section. Significant responses to firm-specific characteristics interacted with the two dummy variables would indicate that credit ratings move in a procyclical manner, while insignificant coefficients on the interacted financial variables can be seen as an indicator of the fact that rating agencies rate "through the cycle". Once again, we will be able to determine whether there is a noticeable influence on the predictive ability of ratings at different stages of the cycle.

## E. Predictive ability

The relative performance of the estimated models is typically evaluated in terms of an informal goodness of fit indicator, by comparing predicted and observed ratings. It is possible, however, to give a more quantitative measure of prediction using the $SC$ and $CP$ scores based on the proportions of correct predictions versus actual outturns.

In a contingency table of actual and predicted ratings the proportion of correct predictions denoted as $SC$ is the sum of all diagonal terms divided by the total number of observations: that is $SC = \frac{1}{T}\sum_{t=1}^{T} 1(\hat{q}_t = q_t)$ where $\hat{q}_t$ refers to the predicted rating and $q_t$ is the actual outcome. This measure is a simple summary of predictive ability, but it is possible that this measure is greatly affected when there is a dominant outcome in the data e.g. if 70% of issuers are rated AA then a prediction of AA for all firms will appear to predict correctly in 70% of cases. This is an illusion since the model does not use the explanatory variables to make different predictions of the probability of rating assignment, but makes only one prediction for all issuers irrespective of the information on business and financial risks. The measure $SC$ cannot distinguish between seemingly successful predictability of a "stopped clock" and true predictability. A second measure based on a technique proposed by Merton (1981) and used in Henriksson and Merton (1981), Pesaran and Timmermann (1994) and Kim et al. (2008) can modify the $SC$ measure in order to get a better indicator of the predictive ability. Let $CP_j$ be the proportion of the correct predictions made by $\hat{q}_t$ when the true state is given by $q_t = j$. From the definition of conditional probability, $CP$ is computed as $CP_j = \dfrac{\frac{1}{T}\sum_{t=1}^{T} 1(\hat{q}_t = j)(q_t = j)}{\frac{1}{T}\sum_{t=1}^{T} 1(q_t = j)}$ and the Merton's correct measure denoted $CP$ is given by $CP = \frac{1}{J-1}[\sum_{j=0}^{J-1} CP_j - 1]$ where $J$ is the number of categories, and $-\frac{1}{J-1} \leq CP \leq 1$. In the contingency table $CP$ is the unweighted average of $CP_j$'s minus one (to correct for the stopped clock phenomenon). The $CP_j$'s are calculated as the proportion of correct predictions divided by the total of each row. This modifies the measure of predictive ability to discount the influence of the dominant outcome. Only when a predictor is accurate for all categories will it obtain a high $CP$ score.

We will use these measures to determine whether the ratings agencies are using information on business and financial risks systematically. If they are then the dynamic ordered probit model should deliver high $SC$ and $CP$ scores, revealing that there is a close correspondence between the information the agencies use and the ratings that they assign.

# III Data and classification methodologies

## A. Data sources

We use Fitch's database as our source for data on issuer default ratings. This database provides information on the long-term rating assigned to each issuer as well as the date that the rating became available. Thus we can record the continuous rating history for each firm. In keeping with the normal practice in the literature, we categorize our firms into rating categories without consideration of notches (i.e + or -). AF (2004), emphasized that this categorization (without taking into account the notches) considers large cumulative changes of ratings, avoids generation of rating categories with very few observations, and sidesteps agencies' practice to change ratings notch by notch. We focus on ratings assigned at the end of December, since balance sheet information for US firms is released on December 31. We consider seven rating categories, ranging from AAA to CCC, which are assigned numerical values, starting with 1 to AAA, 2 to AA,..., 7 to CCC. Due to the fact that there are only a few AAA and CCC ratings we group AAA and AA together creating a "super-investment grade" category, and similarly we group CCC and B ratings together.[7] Table 1 reports the ratings distribution of firms in our sample.

[7] A similar procedure was followed by Calomiris et al. (1995).

We use Datastream to extract firm-level accounting data. The distinguishing characteristic of sampled firms is that they are assigned a long-term rating from Fitch. For these firms, we link their ratings to Datastream's balance sheet statements and profit and loss accounts. Following selection criteria which are common in the literature, we exclude companies that do not have complete records on our explanatory variables and firm-years with negative sales and profits. To control for the potential influence of outliers, we exclude observations in the 0.5 percent from upper and lower tails of the distribution of the regression variables. Data on gross output come from the Bureau of Economic Analysis.

Our combined sample contains data for 317 firm-years yielding a total number of 1906 annual observations. Firms in our sample actively operate between 1995 and 2004 in a variety of sectors such as manufacturing, utilities, resources, services and financials. The panel has an unbalanced structure with the number of observations on each firm varying between three and ten. Our sample presents two characteristics that make it especially appealing for our analysis. First, it includes both investment grade and high yield bonds, where previous studies mainly restricted their attention to investment grade bonds, neglecting the effects of speculative grade bonds.[8] This is particularly beneficial since firms with high yield bond issues are more likely to be characterized by adverse financial attributes and weak balance sheets. Hence, these firms may be subject to more intensive monitoring during recessions. Second, the sample spans a wide range of sectors of the US economy. We use data for five industries: manufacturing, utilities, mining, services and finance. This classification corresponds to the sectoral breakdown of the entire US economy using the Datastream level 3 sector indices, constructed according to the 1999 FTSE reclassification. This is equally important since ratings differ within the context of each issuer's industry fundamentals. In other words, industries that are in decline, highly competitive, capital intensive, cyclical or volatile are inherently riskier than stable industries with few competitors, high barriers to entry, national rather than international competition and predictable demand levels. Therefore, an issuer in a high-risk industry is unlikely to receive the highest rating possible (AAA) despite having a conservative financial profile.

## B. Measures of risks

Rating agencies use a number of indicators in order to assign credit ratings. The criteria for bank ratings are centered on five main areas of fundamental analysis. These include capital adequacy, asset quality, management, earnings and profitability, funding and liquidity (CAMEL). Accordingly, the criteria for corporate ratings consider both business and

[8] In the robustness section, we evaluate the sensitivity of our results by focusing on a sample with investment grade firms only.

financial risks. Business risk can further be divided into industry characteristics and issuer characteristics. The former category includes measures such as prospects and competition, while the latter category involves measures such as diversification, market share and evaluation of management. Financial risk concerns the firm's overall financial policy and is measured using financial ratios. In a special criteria report Fitch emphasize the importance of both types of risk. They state "Fitch's corporate ratings make use of both qualitative and quantitative analysis to assess the business and financial risks of fixed-income issuers." (Fitch (2006a)).

In our empirical model the firm's size, as measured by real total sales, controls for the firm's business risk. A similar proxy was used by a number of empirical papers, see for example Calomiris et al. (1995), BLM (1998) and AF (2004). In addition, we control for business risk by including a variable that proxies for industry competition. Like Ghosal and Loungani (1996) we measure industry competitiveness by the four-firm seller concentration ratio (CR4). This variable is calculated using the percentage of market production supplied by the four largest firms in the industry. Concentration ratios are one of the most common tools used to examine an industry's structure and, consequently, the ability of a group of companies to exercise some control over a market, see Ghosal and Loungani (1996). We expect that higher concentration in a given industry to improve the rating.

As for the financial risk, Fitch considers a number of measures for cash flow, coverage ratio and leverage.[9] We follow Fitch's practice and include a set of variables accounting for financial risk.[10] The first measure is leverage defined as total debt over total assets. This is intended to capture the overall indebtness of the firm. We argue that the higher this ratio the weaker the balance sheet. Therefore, we expect to observe a negative relationship between this variable and credit ratings. The second measure of financial risk is the operating margin, defined as operating profits to net sales. We use this variable to capture the firm's ability to generate profit per unit of sale. We expect higher levels of operating margin to be associated with a stronger balance sheet and therefore better ratings. The third ratio is related to the firm's creditworthiness. We use the interest coverage ratio, as measured by earnings before interest and taxes to interest paid, to assess the firm's ability to generate cash flow in order to pay for financial costs. Increases in this ratio should have a positive effect on the firm's balance sheet and result in improved ratings.[11] Thus we expect a positive coefficient on the

[9] In their words "In conducting financial analysis, Fitch emphasizes cash flow measures of earnings, coverage and leverage [...] Paramount to the analysis is the issuer's ability to generate cash, which is reflected by the ratios that measure profitability and coverage on a cash flow basis" (Fitch (2006a)).

[10] BLM and AF use a similar set of variables but unlike these studies we decide not to include any variables capturing equity risk because Fitch's approach attributes more weight to cash flow measures than equity-based ratios (see Fitch (2006a)).

[11] We checked the robustness of our findings by truncating the interest coverage in order to deal with

coverage ratio. The last measure of financial risk is the interest burden, defined as the ratio of interest payments to total debt. This variable was introduced by Mojon et al. (2002) as a proxy for firm-specific interest rates to examine financial accelerator phenomena.[12] Given that interest rate and credit risk are intrinsically related, we expect firms with higher levels of interest burden to attract lower ratings.

Table 2 reports summary statistics of our explanatory variables. To make our results comparable with previous studies that used data on credit ratings (e.g BLM (1998) and AF (2004)) we report summary statistics as three-year averages for all variables measuring financial risk. This procedure accounts for the fact that rating agencies claim to adopt a longer-term perspective by assigning ratings through the cycle. From Table 2 we observe that firms belonging to the investment grade spectrum are larger, have higher profit margins, lower interest burden, are more creditworthy, less leveraged and have higher *CR4* values compared to high yield firms.

# IV Results

In this section we report the estimation results for the ordered probit models commonly used in the literature and similar to those of BLM (1998), AF (2004) and Alfonso et al. (2007). These are static ordered probit models so we begin by presenting a baseline model of ratings determination that controls for both business and financial risks without dealing with the persistence in the ratings themselves. We then augment the model by including lagged dependent variable and initial observations. Finally, we enrich the dynamic version of the model with variables that aim to capture financing constraints using interaction terms in our empirical specifications to identify the asymmetric effect of the financial constraints. The columns in each table indicate the estimation results for a different classification method.

## A. The static baseline model

Our static baseline empirical model includes a set of financial ratios and industry variables to control simultaneously for business and financial risk. Table 3 presents the results results. Taking the variables proxying for financial risk we observe that both the leverage ($LEV$) and the interest burden ($INTBURD$) have positive coefficients and are highly significant. This result implies that the higher the level of debt to assets and interest payments relative to

skewness. Our main results remain unchanged.

[12] Firm-specific interest rate unlike the Federal Funds rate varies across firms and years and therefore mostly reflects idiosyncratic factors. The obvious advantage of using this measure of interest rates is that it provides large cross-sectional information, which is otherwise hardly available.

total debt, the lower the credit ratings. In addition, the operating margin ($OPER$) and the coverage ratio ($COV$) have negative coefficients showing that creditworthy firms and those with higher profit margins have a higher probability to obtain a better rating (recall that a lower number indicates a higher rating category i.e. 1 = AAA and AA, 2 = A etc). These results are consistent with the existing literature in suggesting that better financial ratios increase the probability of being assigned a better rating (c.f. BLM, 1998; AF, 2004; Gray et al. (2005)). The variables proxying for business risk indicate that the firm's size ($SIZE$) has a higher probability of obtaining a better rating. The concentration ratio ($CR4$) also has a negative coefficient but it is insignificant in the regression. These results are consistent with in-house research by rating agencies and existing evidence.[13]

Overall, the static baseline specification suggests that both business and financial risks are important in determining credit ratings. We point out, however, that the static probit model ignores some important characteristics of the ratings process and the issuers that are rated. First, there is no allowance for the persistence in ratings, which would naturally suggest that the history of ratings would be an important determinant of the current rating. Second, the model does not allow for the distinction between "financially constrained" and "not financially constrained" firms that has been shown to be significant factor in the relationship between firm characteristics and access to credit through bank lending and balance sheet channels, or the investment-agency cost literature. This distinction can be critically important since our explanatory variables have disproportionate effects for different types of firms classified by this criterion. Third, the model does not explore the influence of recessions and credit crunches on the ratings process - and therefore cannot comment on the claim that ratings agencies rate "through the cycle". In the next sub-sections we attempt to capture persistency by introducing variables to the basic model that account for the previous year rating of each firm, we also interact dummies for constraints and recession/crunch with business and financial risks.

## B. Allowing for persistence in ratings

In this section we augment the baseline model and we introduce lagged dummies of each rating category, using category BBB as the reference category, to account for the fact that ratings are generally highly autocorrelated. We estimate the dynamic models allowing for state dependence and accounting for the initial conditions problem. The results for the

[13] As well as controlling for business and financial risks, our model also includes both industry and time dummies. Time dummies were included to capture any business cycle effects. In line with BLM (1998) we observe an increase in the size and significance of our time dummies suggesting that rating agencies have become more stringent over time. AF (2004) also find that in their baseline model, without accounting for trend, time dummies increase in size and significance over time.

dynamic model are presented in Table 4.

On the whole, the estimates are similar to those reported in the previous section in the following respects. We observe that financial variables retain their signs and significance as in the previous (static) specification. In other words, we still find that *LEV* and *INTBURD* have positive coefficients and *OPER* and *COV* have negative coefficients. We draw attention to the coverage ratio, *COV*, which becomes significant at the one percent level. Finally, the firm's size has a negative and highly significant coefficient as before.

The lagged dependent variables - included to formally test for state dependence - are highly statistically significant; therefore if a firm was rated below investment grade in $t$-1 most likely it will remain in the high-yield spectrum in the current period. Likewise, being rated as investment grade in the previous period increases the probability of getting an investment grade rating in the current year. The coefficients on lagged ratings show a clear gradient in the magnitude of the coefficient as one moves from a previous rating status of CC to AAA-AA. In our case the baseline category is lagged BBB. This finding indicates that - for firms issuing bonds with speculative grade status - there is a likelihood of a reduction in the rating value (a higher ordinal value) in the next period, while for firms with investment grade bonds the opposite is true. The estimated coefficients for the initial period observations are also highly significant. This implies that there exists a positive correlation between the initial period observations and unobserved latent creditworthiness.

To sum up, our results suggest that both financial and the business risks continue to be significant influences for the prediction of current credit ratings. Importantly we can report that allowing for the persistence of the ratings process by estimating the model in an ordered probit setting results in highly significant lagged variables reinforcing our beliefs that previous ratings status helps predict current rating status. This finding is potentially significant to both investors and credit ratings agencies because it reveals considerable persistence in ratings. There is strong evidence that the initial rating is also an important determinant of the current rating, in other words, firms rarely transit from investment to sub-investment grade or vice versa. Finally, it is worth noting that there is a substantial improvement in the R-squared indicating a better fit of the model. As we shall see in the next section, these models have a substantially improved predictive ability compared to their static counterparts.

## C. Financial factors and ratings

In this section we use the dummy variable, $C$, linked to firms' relative size, indebtedness and dividend payout compared to the whole distribution of firms on these criteria, to separate firms that are likely to be "financially constrained" and those that are not. We use a 25 percent cut-off point in keeping with the normal practice in the literature. The constrained dummies are interacted with the financial variables to capture the reaction of firm-groups to financial risks when they are also likely to be "financially constrained" compared with the reaction of those firms that are not likely to be "financially constrained". Hence we estimate the model for firm-groups that represent polar tails of the firm distribution. The idea is that the rating process may vary across rating classes. Our goal is to assess whether the financial constraint is a dimension which is taken into account by the credit ratings industry in its ratings methodology.

Comparing across columns in Table 5 allows us to investigate the specific influence of each measure of constrained based on size, dividend payout ratio and level of indebtness on each of the measures of business and financial risk in the rows. Our results are remarkably consistent across these three categories. Taking the leverage variable, $LEV$, we observe that the estimated coefficients are consistently positive and highly significant for firms classified separately as constrained on all three criteria (row1), but are insignificant for unconstrained firms on the same criteria (with the exception of dividend) (row 2). This result highlights a key connection between the impact of leverage on the rating of the firm and the designation "financially constrained". For constrained firms, high leverage can be seen as a sign of a deteriorating balance sheet and therefore increases the probability of a lower rating. For unconstrained firms, the point estimates are statistically insignificant and quantitatively unimportant. This result implies that for constrained firms, leverage issues become more acute than for unconstrained firms.

The influence of $OPER$ on the probability of being in each rating category measures the extent to which high-revenue generation enables firms to be assigned a higher rating. This variable captures a firm's ability to generate profits. The operating margin has a negative coefficient for both types of firms (rows 3 and 4), which is in line with the analysis in section 4.1. It is also statistically significant for both types of firms but with higher coefficients for unconstrained firms. The result that high-revenue generating firms attract better ratings is consistent with evidence presented by other studies (BLM, 1998 and AF, 2004) in which firms with higher profits are more likely to increase their rating. We conclude that profitability is an important determinant for both constrained and unconstrained firms.

Coverage ratio ($COV$) measures the extent to which cash flow is sufficient to pay for financial costs and therefore proxies for creditworthiness. The point estimates are negative for constrained and unconstrained firms (rows 5 and 6) but they are systematically negative and significant only for unconstrained firms (row 6). For unconstrained firms a decrease in creditworthiness has a much larger impact on credit ratings compared to constrained firms, whose credit ratings may have already incorporated the possibility of limited creditworthiness in their balance sheets. We noted earlier than investment grade firms have substantially higher coverage ratios than sub-investment grade firms.

Interest burden (*INTBURD*) measures the impact of the interest rate payments at the firm-level because it reflects the level of the interest rate and the exposure to interest bearing debt but it also reflects the general monetary policy stance since tightening or loosening of policy is reflected in the burden. Comparing the estimated coefficients for interest burden, we observe that they are positive but generally insignificant for both types of firms, except one case (rows 7 and 8). This result implies that a high interest burden increases the probability of a speculative grade rating for both types of firms but its significance is limited.

Our econometric model also includes a set of variables that control for business risks (Size and CR4). We find that larger firms tend to attract higher ratings because they have significant negative coefficients on the size variable. This result confirms the information asymmetry problem that small firms are likely to face, and are consistent with the research line that suggests that high costs of external finance are related to asymmetric information (see Carpenter et al. (1994) and Calomiris and Hubbard (1995)). In other words, we show that larger firms are assigned higher ratings with higher probability because they are associated with the lower degree of informational asymmetry. In addition, we find that the concentration ratio is negative, as in the baseline model, indicating that firms belonging to industries with lower concentration have a higher probability of getting a higher rating but the coefficient is marginally insignificant.[14]

The estimated coefficients of lagged rating categories are, once again, highly statistically significant. Even allowing for firms classified as likely to be "financially constrained" or not, does not undermine the persistence in ratings. We find that being assigned an investment grade rating (AAA-AA, A, BBB) in the previous period increases the probability of getting an investment grade rating in the current year. The same applies for speculative grade rating. This result clearly indicates that rating assignment in the previous year is closely associated with the rating obtained in the following year, even allowing for the impact of characteristics such as being financially constrained on the basis of indicator such as relative size or indebtedness which are themselves persistent.

[14] We also include a set of time dummies to control for common trends and business cycle effects, and a set of industry dummies to control for fixed effects across industries. Once again, we observe that time dummies are significant and increase over time showing that credit standards have become, on average, worse over time for firms under scrutiny. Industry dummies are also significant indicating that industry-level differences are significant in predicting credit ratings.

## D. The procyclicality of ratings

Whether credit ratings are procyclical or not is an open question. Previous evidence suggests procyclicality of credit quality changes by showing that estimated credit losses are much higher in contractions relative to expansions (see Bangia et al. (2002)). Nickell et al. (2000) find that default probabilities depend on the business cycle with lower rated firms being affected the most. However, rating agencies claim that credit ratings do not vary with the cycle: in other words they "rate through the cycle" (see Moody's (2002) and Fitch (2006a)). AF (2004) do not detect any excessive procyclicality in ratings assignments and implicitly assume that any procyclicality is driven by cyclical changes to business and financial risks, and not by business cycle-related changes to rating standards.

This section addresses the issue of procyclality of ratings by examining the sensitivity of ratings to balance sheet variables in the 2001-02 recession/credit crunch episode versus other times. To explore the response to firm-specific characteristics when the economy is in recession/credit crunch we interact the explanatory variables with a recession/credit crunch dummy, $D$. Table 6 reports coefficients on variables interacted with the dummy variable $D$ (recession/credit crunch) and interacted with 1-$D$ (out of recession/credit crunch) for constrained and unconstrained firms.

Results are reported in Table 6. When the recession/credit crunch dummy is interacted with constrained and unconstrained firms we observe that financial variables for both types of firms are more sensitive outside the recession/credit crunch, 1-$D$. Ratings vary more with these business and financial risks outside of recession/crunch than they do when there is a recession/crunch. There are slightly larger coefficients on *LEV*, *OPER* and *INTBURD* for non-recession/crunch periods compared with recession/crunch periods but in most cases these are not significant differences. We conclude that the 2001-02 recession/credit crunch had little impact on credit ratings in the US bond market, in agreement with Amato and Furfine's result that ratings do not exhibit a substantial degree of comovement with business cycles/credit crunches. We do find evidence that leverage is significant during recessions for constrained firms indicating that financing constraints are more binding for financially weak firms.

# V Model Predictions

This section evaluates the predictive ability of the ordered probit models presented in section 4. We start by presenting in-sample predictions but we also carry out an out-of-sample exercise to get a more realistic assessment of the actual predictive power of the estimated models.

## A. In-sample predictions

A standard way of measuring the goodness of fit of ordered probit models is the construction of contingency tables where one can compare predicted ratings to actual ratings. The outcome of this exercise is shown in Tables 7 and 8 which correspond to the estimated models in section 4. Reading across each row gives the number of predicted observations per category against the actual outcome in the leftmost column. For example, the first row shows the number of observations with actual rating of AAA-AA, while the second row those with rating A etc. To correctly evaluate the predictive ability of our model we employ two different statistics, $SC$ and $CP$. We expect the former statistic to be influenced by any dominant outcome in the data while the latter is corrected for this problem.

We begin by comparing results using the baseline model shown in Table 7. We observe that the baseline model correctly predicts AAA-AA 58 times, A 594 times, BBB 334 times, BB 14 times and B 0 times. There are 1000 occasions when the correct prediction is made, hence we find that the $SC = 1000/1737$, which suggests that we have approximately 57 percent correct predictions. The outcome of this exercise highlights two important issues. First, that the result obtained may be artificially high and driven by dominant outcomes in the data. In our case A is the dominant category and therefore it is possible that our results are due to this outcome. Second, that these results reflect a common feature of static ordered probit models in that the highest and the lowest categories are underestimated.

To circumvent the first problem we allow for the dominant outcome by reporting the Merton correct predictions statistic. This test calculates correct predictions using the proportion of correct predictions for each of the five rating categories: $CP_1 = 58/235$, $CP_2 = 594/786$, $CP_3 = 334/556$, $CP_4 = 14/134$ and $CP_5 = 0/26$. This test implies that $CP = 0.17$, which shows a lower but still reasonable predictive ability of our model.[15]

As for the model's underprediction for firms of low credit quality relative to higher credits, we follow a dynamic approach since it is likely that the relative poor performance of the model is due to the fact that it does not take account of the persistence of ratings. If this is the case, we would expect a substantial improvement when we add dynamics in the ordered probit model.

Our model predictions using the dynamic ordered probit models are reported in Table 8. We find that the proportion of correct predictions against the actual outcomes is $SC = 1465/1551$, indicating approximately 94 percent of predictions is correct. Comparing this

[15] Amato and Furfine's model attains similar scores for the statistics, namely $SC$=0.52 and $CP$=0.26 for the model with time dummies.

statistic with the Merton correct prediction we find $CP = 0.89$, which shows a substantial improvement in the predictive ability of the model. The results reveal that the dynamic model outperforms the static one by far, showing an impressive improvement on both statistics. In addition, we no longer observe any overrating or underrating in the model predictions. The AAA-AA category predicts 170 cases out of 209 actuals - a remarkably high score, and B-CC predicts 16 out of 19. The main conclusion that can be drawn from this exercise is that credit ratings are indeed highly autocorrelated and previous years' ratings are a key variable when predicting current ratings.

Similar results are found for the model which is augmented with dummy variables proxying for financial constraints and for recessions/crunches. The $SC$ statistic indicates correct prediction around the region of 95 percent, whereas the $CP$ statistic correctly predicts in 90 percent of cases. Both tests are reported at the foot of the corresponding Tables.

## B. Out-of-sample predictions

This section presents out-of-sample predictions of ratings using the past and current information available up to time $T$. We use an expanding window method, which allows the successive observations to be included in the initial sample prior to forecast of the next one-step ahead prediction of the rating while keeping the start date of the sample fixed. By this method, we forecast future ratings $\hat{q}_{t+1}$, $\hat{q}_{t+2}$ etc. The initial estimation window is 1995 to 2000 and the first prediction date is year 2001. We then increase $T$ by one each time until $T$ reaches year 2004.

Table 9 shows the cross-tabulations of the predicted against observed outcomes using the baseline (static) model presented in section 4.1. As with the in-sample predictions we find that the baseline model has a reasonable predictive ability. Computing the SC statistic we get a figure of 0.43 and the Merton correct prediction measure indicates CP=0.14. As noted in the previous section, we expect a improvement in the predictive accuracy of the model once we capture persistence in ratings.

Table 10 illustrates the contingency table of the predicted against actual outcome out-of-sample results for the dynamic model presented in section 4.2. As with the in-sample results, the predictive ability of the out-of-sample predictions improve when dynamics are included, since SC=0.70 per cent and the Merton correct prediction statistic indicates CP=0.54. This is much better than the corresponding figures for the out-of-sample exercise using a static model.

Summarizing, we find ratings persistence leads to more accurate predictions of credit ratings compared to the static model. This is the case for both in-sample and out-of sample predictions.

# VI Robustness tests

We now test the robustness of our previous findings. These additional checks involve estimation of our empirical model with an alternative sample selection and employing random effects. The former test attempts to ensure that our model is not misspecified by using a sample of both investment grade and high yield firms. The latter test checks the sensitivity of our results when we use the random effects probit model to control for unobserved heterogeneity. This methodology differs from the previous (pooled probit) approach since we allow the residuals to have a random effects structure.

## A. Investment grade ratings

The vast majority of previous studies on ratings determination employ only data for investment grade firms; in our previous results we use both investment and speculative grade firms. This is an advantage since firms with speculative grade bonds are more likely to be subject to financing constraints, and as noted by AF (2004), restricting attention to investment grade issuers only is likely to induce selection bias. However, pooling together both categories may result in misspecification of our model if changes in financial and business risk have a different impact on rating determination across the two groups of firms. In order to determine whether our results are affected by this bias we drop all speculative grade firms and using only firms with investment grade bonds we re-estimate the original model.

Results for the ordered probit models are shown in Table 11. Once again, we observe positive coefficients for $LEV$ and negative for $OPER$ for both constrained and unconstrained categories. The coefficients on leverage are significant for constrained firms in all three cases, while the point estimates on operating margin are significant for both categories. Both results are in line with those reported earlier. For the variables $COV$ and $INTBURD$ the former retains its significance for unconstrained firms, while the latter financial variable is generally insignificant for both types of firms. Finally, the lagged dependent variables remain highly significant suggesting that a downgrade (upgrade) is more likely to be followed by a subsequent downgrade (upgrade). Overall, we observe that our results remain largely unchanged by interacting the dummy variable and our earlier results are therefore robust to this modification.

## B. Random effects probits

In our main results we employed pooled ordered probit estimates to assess the impact of financial factors on credit ratings. It could be argued that the pooled models do not explicitly take into consideration the panel nature of the dataset and ignore potential unobserved time invariant heterogeneity (since we have repeated observations for every firm). To address this issue we can employ random effects methods, but the downside of this method is that it is conditioned on the strict exogeneity assumptions, which may not be valid. In this section we re-estimate the baseline model augmented with financing constraints using the random effects ordered probit method. Results for the random effects ordered probit models are reported in Table 12.

It is apparent that our results both quantitatively and qualitatively remain largely unchanged. We still find the estimated coefficients on $LEV$ to be positive and highly significant for firms classified as constrained (with the exception of dividend), but insignificant for unconstrained firms. Once again, $OPER$ has a coefficient that is negative and highly significant for both types of firms, and for $COV$ and $INTBURD$ we observe the former variable has a negative and significant coefficient for unconstrained firms as before, while the latter variable has a coefficient that remains positive but looses its significance for both types of firms. The influence of lagged dependent variables remains strongly significant confirming the persistence in ratings. Taking these results into consideration, we can conclude that modeling credit ratings using random effects methods does not make a substantial difference, suggesting that our results are not a by-product of not taking into account the unobserved heterogeneity.

# VII Conclusion

Recent events have drawn attention to credit rating agencies and their procedures, and many questions are being asked about the reliability of their ratings. In this paper we ask how the ratings relate to underlying business and financial risks. Our first finding is that these are very important determinants of ratings. A baseline model of rating determination that accounts for both business and financial risks predicts ratings with moderate success.

The existing literature on ratings predictions has focused on a set of financial ratios usually incorporated in a static ordered probit setting, but there is strong evidence to suggest there is persistence in ratings. Indeed ratings agencies claim to "rate through the cycle". This paper recognizes the persistence property of credit ratings and examines their determinants by augmenting the standard ordered probit models of the ratings predictions with lagged dependent variables and when we introduce dynamics in the ordered probit estimation we document an impressive increase in the predictive power of the model, which indicates that modeling ratings persistence is an important consideration. We then consider whether constrained and unconstrained firms are rated differently and whether ratings change between recession/credit crunch periods and non-recession/credit crunch periods, which addresses the issue of procyclicality of ratings. We show that financial variables have a differential impact on firm-types in predicting credit ratings, depending on whether firms are likely to face binding financing constraints and financial variables do not appear to be more important during recession/credit crunch compared to other periods. Our results indicate that rating agencies provide ratings which are stable over time, lending support to the "through the cycle" methodology. These results are robust to alternative sample selections, different estimation techniques, many specifications and controls.

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Table 1
Ratings per year

| | AAA | AA | A | BBB | BB | B | CCC | Observations |
|---|---|---|---|---|---|---|---|---|
| 1995 | 0 | 19 | 45 | 13 | 5 | 1 | 0 | 83 |
| 1996 | 0 | 23 | 56 | 17 | 4 | 2 | 0 | 102 |
| 1997 | 1 | 23 | 64 | 28 | 7 | 2 | 0 | 125 |
| 1998 | 1 | 25 | 67 | 41 | 10 | 3 | 0 | 147 |
| 1999 | 1 | 24 | 69 | 54 | 10 | 2 | 0 | 160 |
| 2000 | 1 | 30 | 85 | 64 | 10 | 4 | 0 | 194 |
| 2001 | 2 | 30 | 100 | 80 | 18 | 3 | 0 | 233 |
| 2002 | 2 | 27 | 109 | 94 | 27 | 3 | 1 | 264 |
| 2003 | 4 | 25 | 103 | 102 | 34 | 7 | 0 | 285 |
| 2004 | 4 | 27 | 120 | 120 | 33 | 7 | 2 | 313 |
| *Observations* | 16 | 253 | 828 | 613 | 158 | 34 | 3 | 1906 |

Notes: The table presents the distribution of firms' ratings by year based on a panel of firms from 1995 through 2004.

TABLE 2
STATISTICS

| | Mean | 0.25 | Median | 0.75 |
|---|---|---|---|---|
| **LEV** | | | | |
| $AAA-AA$ | 24.79 | 4.87 | 14.87 | 31.95 |
| $A$ | 25.44 | 14.75 | 23.56 | 34.21 |
| $BBB$ | 32.61 | 22.60 | 32.44 | 42.27 |
| $BB$ | 40.35 | 30.18 | 40.05 | 48.49 |
| $B-CC$ | 46.84 | 35.07 | 46.48 | 60.51 |
| $Total$ | 29.03 | 16.47 | 26.95 | 39.74 |
| **INTBURD** | | | | |
| $AAA-AA$ | 0.05 | 0.01 | 0.02 | 0.08 |
| $A$ | 0.08 | 0.02 | 0.05 | 0.08 |
| $BBB$ | 0.10 | 0.01 | 0.03 | 0.07 |
| $BB$ | 0.14 | 0.01 | 0.02 | 0.08 |
| $B-CC$ | 0.10 | 0.02 | 0.04 | 0.07 |
| $Total$ | 0.09 | 0.02 | 0.04 | 0.08 |
| **COV** | | | | |
| $AAA-AA$ | 12.56 | 4.20 | 7.91 | 13.97 |
| $A$ | 9.43 | 3.37 | 5.80 | 10.27 |
| $BBB$ | 7.35 | 2.31 | 3.53 | 6.89 |
| $BB$ | 4.39 | 1.66 | 2.33 | 4.58 |
| $B-CC$ | 2.34 | 1.02 | 1.64 | 2.43 |
| $Total$ | 11.08 | 2.76 | 5.10 | 10.03 |
| **OPER** | | | | |
| $AAA-AA$ | 23.29 | 13.71 | 19.39 | 25.62 |
| $A$ | 17.09 | 9.71 | 15.06 | 22.62 |
| $BBB$ | 15.26 | 7.60 | 12.95 | 21.03 |
| $BB$ | 14.17 | 5.91 | 11.28 | 15.94 |
| $B-CC$ | 10.37 | 5.47 | 9.73 | 12.33 |
| $Total$ | 16.25 | 8.32 | 13.60 | 21.83 |
| **SIZE** | | | | |
| $AAA-AA$ | 11.60 | 10.67 | 11.76 | 12.74 |
| $A$ | 11.09 | 10.24 | 11.07 | 11.92 |
| $BBB$ | 10.74 | 9.83 | 10.79 | 11.79 |
| $BB$ | 10.46 | 9.67 | 10.57 | 11.31 |
| $B-CC$ | 10.12 | 9.59 | 10.29 | 10.96 |
| $Total$ | 10.94 | 9.92 | 10.84 | 11.81 |
| **CR4** | | | | |
| $AAA-AA$ | 12.48 | 8.34 | 11.75 | 16.71 |
| $A$ | 13.85 | 10.88 | 11.78 | 20.80 |
| $BBB$ | 12.17 | 7.39 | 11.31 | 19.03 |
| $BB$ | 11.12 | 7.26 | 11.09 | 11.86 |
| $B-CC$ | 9.91 | 6.06 | 8.63 | 11.71 |
| $Total$ | 11.88 | 8.11 | 11.31 | 13.84 |

Notes: The table presents percentile distribution. LEV= Total debt over total assets, INTBURD= Interest payments over total assets, COV= Earnings before interest and taxes to interest paid, OPER= Operating profits to net sales, SIZE= Real total sales, CR4= The four-firm seller concentration ratio.

TABLE 3
THE BASELINE MODEL

| | |
|---|---|
| *LEV* | 0.027*** |
| | (11.4) |
| *OPER* | -0.044*** |
| | (-11.3) |
| *COV* | -0.007* |
| | (-1.71) |
| *INTBURD* | 0.089*** |
| | (6.60) |
| *SIZE* | -0.478*** |
| | (-17.6) |
| *CR*4 | -0.002 |
| | (-0.13) |
| $R^2$ | 0.21 |
| *SC* | 0.57 |
| *CP* | 0.17 |

Notes: The table presents ordered probit estimation results. The left-hand side variable is the credit rating of a firm. In the analysis AAA-AA ratings are assigned a "1", A a "2", and so on until CC ratings, which are assigned a "5". Time dummies and industry dummies were included in all specifications. Number of firms and observations are 308 and 1737, respectively. Robust z-statistics are reported in the parentheses. SC stands for the "stopped clock" statistic, and CP for the "correct prediction" statistic. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4
Dynamic Model

| | |
|---|---|
| $LEV$ | 0.016*** |
| | (6.12) |
| $OPER$ | -0.036*** |
| | (-5.94) |
| $COV$ | -0.019*** |
| | (-3.64) |
| $INTBURD$ | 0.005 |
| | (0.26) |
| $AAA-AA\_1$ | -3.561*** |
| | (-8.77) |
| $A\_1$ | -2.465*** |
| | (-12.5) |
| $BB\_1$ | 5.341*** |
| | (4.80) |
| $B-CC\_1$ | 23.865*** |
| | (15.7) |
| $AAA-AA(1)$ | -3.119*** |
| | (-9.95) |
| $A(1)$ | -1.162*** |
| | (-6.96) |
| $BB(1)$ | 1.266*** |
| | (2.60) |
| $B-CC(1)$ | 0.298* |
| | (1.86) |
| $SIZE$ | -0.499*** |
| | (-11.4) |
| $CR4$ | -0.014 |
| | (-0.54) |
| $SC$ | 0.94 |
| $CP$ | 0.89 |

Notes: The table presents dynamic ordered probit estimation results. The left-hand side variable is the credit rating of a firm. In the analysis AAA-AA ratings are assigned a "1", A a "2", and so on until CC ratings, which are assigned a "5". The one period lags of the ratings are reported as AAA-AA_1 etc. The initial period observations are reported as AAA-AA(1) etc. Time dummies and industry dummies were included in all specifications. Number of firms and observations are 296 and 1551, respectively. Robust z-statistics are reported in the parentheses. SC stands for the "stopped clock" statistic, and CP for the "correct prediction" statistic. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 5
FINANCIAL CONSTRAINTS

| | INDEBT | DIVID | SIZE |
|---|---|---|---|
| $LEV * C$ | 0.011** | 0.014*** | 0.045*** |
| | (2.50) | (2.99) | (7.26) |
| $LEV * (1 - C)$ | -0.009 | 0.010* | 0.004 |
| | (-0.76) | (1.77) | (1.17) |
| $OPER * C$ | -0.013** | -0.012 | -0.014*** |
| | (-2.10) | (-1.31) | (-3.32) |
| $OPER * (1 - C)$ | -0.024*** | -0.017* | -0.065*** |
| | (-2.62) | (-1.65) | (-5.24) |
| $COV * C$ | -0.009 | -0.004 | -0.007 |
| | (-0.87) | (-0.42) | (-1.26) |
| $COV * (1 - C)$ | -0.012** | -0.030*** | -0.025** |
| | (-2.15) | (-3.10) | (-2.38) |
| $INTBURD * C$ | 0.028 | 0.023 | -0.054*** |
| | (0.94) | (1.07) | (-2.84) |
| $INTBURD * (1 - C)$ | 0.044 | 0.021 | -0.020 |
| | (1.58) | (0.62) | (-0.70) |
| $AAA - AA\_1$ | -3.099*** | -4.143*** | -4.130*** |
| | (-9.35) | (-11.0) | (-10.9) |
| $A\_1$ | -2.523*** | -2.670*** | -2.701*** |
| | (-11.9) | (-14.1) | (-14.1) |
| $BB\_1$ | 5.298*** | 5.581*** | 5.175*** |
| | (4.53) | (4.97) | (4.81) |
| $B - CC\_1$ | 15.107*** | 14.452*** | 21.279*** |
| | (25.2) | (27.2) | (14.6) |
| $AAA - AA(1)$ | -3.428*** | -3.357*** | -3.069*** |
| | (-9.27) | (-9.03) | (-9.97) |
| $A(1)$ | -1.679*** | -1.580*** | -1.085*** |
| | (-13.6) | (-12.4) | (-6.91) |
| $BB(1)$ | 1.838*** | 1.957*** | 1.357*** |
| | (8.83) | (9.96) | (2.91) |
| $B - CC(1)$ | 2.468*** | 2.591*** | 0.472** |
| | (4.08) | (4.34) | (2.55) |
| $SIZE$ | -0.212*** | -0.225*** | -0.502*** |
| | (-5.20) | (-5.46) | (-5.02) |
| $CR4$ | -0.035 | -0.032 | 0.010 |
| | (-1.61) | (-1.44) | (0.38) |
| $SC$ | 0.95 | 0.95 | 0.94 |
| $CP$ | 0.90 | 0.91 | 0.90 |

Notes: The table presents dynamic ordered probit estimation results. The left-hand side variable is the credit rating of a firm. In the analysis AAA-AA ratings are assigned a "1", A a "2", and so on until CC ratings, which are assigned a "5". The dummy variable C indicates in turn HIGHLY INDEBTED, LOW DIVIDEND and SMALL firms. The one period lags of the ratings are reported as AAA-AA_1 etc. The initial period observations are reported as AAA-AA(1) etc. Time dummies and industry dummies were included in all specifications. Number of firms and observations are 296 and 1551, respectively. Robust z-statistics are reported in the parentheses. SC stands for the "stopped clock" statistic, and CP for the "correct prediction" statistic. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 6
PROCYCLICALITY

| | INDEBT | DIVID | SIZE |
|---|---|---|---|
| $LEV * C * D$ | 0.014*** | 0.044*** | 0.011** |
| | (2.58) | (4.16) | (2.21) |
| $LEV * C * (1 - D)$ | 0.017*** | 0.042*** | -0.000 |
| | (4.46) | (5.67) | (-0.037) |
| $LEV * (1 - C) * D$ | 0.047** | 0.011 | 0.043*** |
| | (2.01) | (1.55) | (3.53) |
| $LEV * (1 - C) * (1 - D)$ | -0.022 | 0.018* | 0.047*** |
| | (-1.00) | (1.94) | (7.29) |
| $OPER * C * D$ | -0.024*** | -0.091*** | -0.015** |
| | (-2.78) | (-3.18) | (-2.30) |
| $OPER * C * (1 - D)$ | -0.029*** | -0.093*** | -0.015*** |
| | (-5.03) | (-4.41) | (-3.91) |
| $OPER * (1 - C) * D$ | -0.017* | -0.018** | -0.049*** |
| | (-1.81) | (-2.09) | (-2.88) |
| $OPER * (1 - C) * (1 - D)$ | -0.037*** | -0.039*** | -0.065*** |
| | (-3.01) | (-2.97) | (-4.41) |
| $COV * C * D$ | -0.005 | -0.045 | -0.001 |
| | (-0.41) | (-0.75) | (-0.12) |
| $COV * C * (1 - D)$ | -0.008* | 0.042 | -0.005 |
| | (-1.72) | (1.53) | (-1.03) |
| $COV * (1 - C) * D$ | 0.005 | -0.002 | -0.012 |
| | (1.12) | (-0.21) | (-0.97) |
| $COV * (1 - C) * (1 - D)$ | -0.009 | -0.024*** | -0.015* |
| | (-1.52) | (-2.96) | (-1.66) |
| $INTBURD * C * D$ | 0.024 | -0.042 | -0.073*** |
| | (0.61) | (-0.71) | (-3.35) |
| $INTBURD * C * (1 - D)$ | 0.015 | -0.027 | -0.031* |
| | (0.81) | (-0.83) | (-1.66) |
| $INTBURD * (1 - C) * D$ | -0.079 | 0.002 | -0.069 |
| | (-1.35) | (0.039) | (-1.04) |
| $INTBURD * (1 - C) * (1 - D)$ | 0.095* | 0.027 | -0.027 |
| | (1.75) | (0.48) | (-0.89) |
| $AAA - AA\_1$ | -3.842*** | -4.384*** | -4.254*** |
| | (-9.15) | (-11.2) | (-10.6) |
| $A\_1$ | -2.517*** | -2.856*** | -2.759*** |
| | (-12.6) | (-14.4) | (-13.9) |
| $BB\_1$ | 5.315*** | 5.756*** | 5.146*** |
| | (4.53) | (5.16) | (4.82) |
| $B - CC\_1$ | 22.276*** | 28.342*** | 21.121*** |
| | (13.7) | (12.1) | (14.6) |
| $AAA - AA(1)$ | -3.066*** | -3.031*** | -2.969*** |
| | (-9.48) | (-8.80) | (-8.79) |
| $A(1)$ | -1.184*** | -1.053*** | -1.052*** |
| | (-7.56) | (-5.53) | (-6.46) |
| $BB(1)$ | 1.195** | 1.278*** | 1.362*** |
| | (2.17) | (3.53) | (2.85) |
| $B - CC(1)$ | 0.471** | 0.387* | 0.496*** |
| | (2.18) | (1.74) | (2.61) |
| $SIZE$ | -0.413*** | -0.420*** | -0.491*** |
| | (-10.6) | (-11.1) | (-5.35) |
| $CR4$ | 0.012 | 0.019 | 0.007 |
| | (0.47) | (0.49) | (0.27) |
| $SC$ | 0.94 | 0.95 | 0.94 |
| $CP$ | 0.90 | 0.91 | 0.90 |

Notes: The table presents dynamic ordered probit estimation results. The left-hand side variable is the credit rating of a firm. In the analysis AAA-AA ratings are assigned a "1", A a "2", and so on until CC ratings, which are assigned a "5". The dummy variable C indicates in turn LESS INDEBTED, LOW DIVIDEND and SMALL firms. The dummy variable D indicates recession/credit crunch. The one period lags of the ratings are reported as AAA-AA_1 etc. The initial period observations are reported as AAA-AA(1) etc. Time dummies and industry dummies were included in all specifications. Number of firms and observations are 296 and 1551, respectively. Robust z-statistics are reported in the parentheses. SC stands for the "stopped clock" statistic, and CP for the "correct prediction" statistic. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 7
IN-SAMPLE STATIC

| Actual Rating | Predicted Rating | | | | | |
|---|---|---|---|---|---|---|
| | AAA-AA | A | BBB | BB | B-CC | Total |
| $AAA-AA$ | 58 | 171 | 6 | 0 | 0 | 235 |
| $A$ | 38 | 594 | 151 | 3 | 0 | 786 |
| $BBB$ | 0 | 220 | 334 | 2 | 0 | 556 |
| $BB$ | 1 | 20 | 97 | 14 | 2 | 134 |
| $B-CC$ | 0 | 2 | 17 | 7 | 0 | 26 |
| $Total$ | 97 | 1007 | 605 | 26 | 2 | 1,737 |
| $SC = 0.57, CP = 0.17$ | | | | | | |

Notes: The table reports in-sample predictions of the static ordered probit model. The leftmost column shows actual ratings while the righthand side columns show the prediction of the static ordered probit.

TABLE 8
IN-SAMPLE DYNAMIC

| Actual Rating | Predicted Rating | | | | | |
|---|---|---|---|---|---|---|
| | AAA-AA | A | BBB | BB | B-CC | Total |
| $AAA-AA$ | 170 | 39 | 0 | 0 | 0 | 209 |
| $A$ | 14 | 628 | 9 | 1 | 0 | 652 |
| $BBB$ | 0 | 17 | 539 | 0 | 0 | 556 |
| $BB$ | 0 | 0 | 0 | 112 | 3 | 115 |
| $B-CC$ | 0 | 0 | 3 | 0 | 16 | 19 |
| $Total$ | 184 | 684 | 551 | 113 | 19 | 1,551 |
| $SC = 0.94, CP = 0.89$ | | | | | | |

Notes: The table reports in-sample predictions of the dynamic ordered probit model. The leftmost column shows actual ratings while the righthand side columns show the prediction of the dynamic ordered probit.

TABLE 9
OUT-OF-SAMPLE STATIC

| Actual Rating | Predicted Rating | | | | | |
|---|---|---|---|---|---|---|
| | AAA-AA | A | BBB | BB | B-CC | Total |
| $AAA-AA$ | 70 | 33 | 1 | 0 | 0 | 104 |
| $A$ | 96 | 301 | 13 | 0 | 0 | 410 |
| $BBB$ | 14 | 296 | 52 | 0 | 0 | 362 |
| $BB$ | 1 | 55 | 35 | 1 | 0 | 92 |
| $B-CC$ | 0 | 6 | 9 | 0 | 0 | 15 |
| $Total$ | 181 | 691 | 110 | 1 | 0 | 983 |
| $SC = 0.43, CP = 0.14$ | | | | | | |

Notes: The table reports out-of-sample predictions of the static ordered probit model. The leftmost column shows actual ratings while the righthand side columns show the prediction of the static ordered probit.

TABLE 10
OUT-OF-SAMPLE DYNAMIC

| Actual Rating | Predicted Rating | | | | | |
|---|---|---|---|---|---|---|
| | AAA-AA | A | BBB | BB | B-CC | Total |
| $AAA-AA$ | 94 | 0 | 0 | 0 | 0 | 94 |
| $A$ | 196 | 173 | 0 | 0 | 0 | 369 |
| $BBB$ | 0 | 52 | 310 | 0 | 0 | 362 |
| $BB$ | 0 | 0 | 16 | 67 | 0 | 83 |
| $B-CC$ | 0 | 0 | 0 | 12 | 1 | 13 |
| $Total$ | 290 | 225 | 326 | 79 | 1 | 921 |
| $SC = 0.70, CP = 0.54$ | | | | | | |

Notes: The table reports out-of-sample predictions of the dynamic ordered probit model. The leftmost column shows actual ratings while the righthand side columns show the prediction of the dynamic ordered probit.

TABLE 11
INVESTMENT GRADE

| | INDEBT | DIVID | SIZE |
|---|---|---|---|
| $LEV*C$ | 0.019*** | 0.035*** | 0.058*** |
| | (2.79) | (5.27) | (7.39) |
| $LEV*(1-C)$ | -0.027 | 0.017* | 0.002 |
| | (-1.31) | (1.91) | (0.35) |
| $OPER*C$ | -0.031*** | -0.090*** | -0.001 |
| | (-3.26) | (-4.15) | (-0.50) |
| $OPER*(1-C)$ | -0.029* | -0.025*** | -0.073*** |
| | (-1.93) | (-2.72) | (-4.66) |
| $COV*C$ | -0.000 | 0.010 | -0.019* |
| | (-0.039) | (0.26) | (-1.68) |
| $COV*(1-C)$ | -0.017* | -0.037*** | -0.019* |
| | (-1.93) | (-3.09) | (-1.68) |
| $INTBURD*C$ | 0.021 | 0.013 | -0.035** |
| | (0.62) | (0.38) | (-2.33) |
| $INTBURD*(1-C)$ | 0.100 | 0.027 | -0.108*** |
| | (1.60) | (0.42) | (-3.06) |
| $AAA-AA\_1$ | -3.858*** | -4.185*** | -4.506*** |
| | (-3.93) | (-10.9) | (-11.22) |
| $BBB\_1$ | -2.690*** | -2.841*** | -3.212*** |
| | (-6.34) | (-15.0) | (-19.69) |
| $AAA-AA(1)$ | -2.084*** | -2.086*** | -2.146*** |
| | (-4.87) | (-9.52) | (-9.22) |
| $BBB(1)$ | 1.278*** | 1.294*** | 1.839*** |
| | (6.02) | (9.90) | (14.7) |
| $SIZE$ | -0.463*** | -0.431*** | -0.260*** |
| | (-5.96) | (-9.83) | (-4.81) |
| $CR4$ | 0.018 | 0.008 | 0.006 |
| | (0.84) | (0.30) | (0.24) |

Notes: The table presents dynamic ordered probit estimation results. The left-hand side variable is the credit rating of a firm. In the analysis AAA-AA ratings are assigned a "1", A a "2", and so on until CC ratings, which are assigned a "5". The dummy variable C indicates in turn LESS INDEBTED, LOW DIVIDEND and SMALL firms. The one period lags of the ratings are reported as AAA-AA_1 etc. The initial period observations are reported as AAA-AA(1) etc. Time dummies and industry dummies were included in all specifications. Number of firms and observations are 270 and 1398, respectively. Robust z-statistics are reported in the parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12
Random effects

| | INDEBT | DIVID | SIZE |
|---|---|---|---|
| $LEV * C$ | 0.034*** | 0.019 | 0.052*** |
| | (2.75) | (1.60) | (3.36) |
| $LEV * (1 - C)$ | 0.021 | 0.015 | 0.019 |
| | (1.05) | (1.24) | (1.63) |
| $OPER * C$ | -0.016 | -0.051* | -0.058*** |
| | (-0.92) | (-1.67) | (-2.79) |
| $OPER * (1 - C)$ | -0.036** | -0.025 | -0.028 |
| | (-2.04) | (-1.54) | (-1.63) |
| $COV * C$ | -0.036 | 0.029 | 0.024 |
| | (-1.17) | (0.63) | (1.18) |
| $COV * (1 - C)$ | -0.007 | -0.032** | -0.073*** |
| | (-0.52) | (-2.15) | (-4.78) |
| $INTBURD * C$ | -0.103 | 0.085 | -0.099 |
| | (-1.44) | (1.30) | (-1.42) |
| $INTBURD * (1 - C)$ | 0.006 | 0.048 | 0.025 |
| | (0.14) | (0.88) | (0.52) |
| $AAA - AA\_1$ | -13.652 | -20.965 | -14.611 |
| | (-0.035) | (-0.021) | (-0.046) |
| $A\_1$ | -1.003*** | -0.966*** | -1.005*** |
| | (-7.02) | (-6.65) | (-6.71) |
| $BB\_1$ | 9.288*** | 9.456*** | 9.743*** |
| | (10.6) | (10.3) | (10.4) |
| $B - CC\_1$ | 32.227 | 32.963 | 34.694 |
| | (0.008) | (0.000) | (0.008) |
| $AAA - AA(1)$ | -8.845*** | -8.498*** | -9.336*** |
| | (-13.9) | (-14.1) | (-12.9) |
| $A(1)$ | -3.795*** | -3.504*** | -4.169*** |
| | (-11.1) | (-9.66) | (-9.59) |
| $BB(1)$ | 1.264 | 1.902** | 1.302 |
| | (1.36) | (2.09) | (1.36) |
| $B - CC(1)$ | -1.751* | 0.725 | -1.847* |
| | (-1.74) | (0.27) | (-1.72) |
| $SIZE$ | -0.271*** | -0.308*** | -0.184 |
| | (-3.53) | (-3.92) | (-1.38) |
| $CR4$ | 0.051 | 0.047 | 0.062* |
| | (1.54) | (1.43) | (1.80) |

Notes: The table presents dynamic random effects ordered probit estimation results. The left-hand side variable is the credit rating of a firm. In the analysis AAA-AA ratings are assigned a "1", A a "2", and so on until CC ratings, which are assigned a "5". The dummy variable C indicates in turn LESS INDEBTED, LOW DIVIDEND and SMALL firms. The one period lags of the ratings are reported as AAA-AA_1 etc. The initial period observations are reported as AAA-AA(1) etc. Time dummies and industry dummies were included in all specifications. Number of firms and observations are 296 and 1551, respectively. Robust z-statistics are reported in the parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

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