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Statistical properties and stability of ratings in a subset of US firms

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Statistical properties and stability of ratings in a subset of US firms*

Alexander B. Matthies†

Abstract

Standard explanatory variables that determine credit ratings do not achieve significant effects in a sample of 100 US non-financial firms in an ordered probit panel estimation. Sample size and selection as well as the distribution of explanatory variables across rating classes may be the cause this problem. Furthermore, we find evidence to suggest that variable coefficients vary over rating classes when analysed with an unordered loogit model. The sample reproduces well-established macroeconomic effects of credit ratings found by Blume et al. (1998) and highlights the influence of the rating agencies' through-the-cycle approach on rating transitions.

Keywords: Rating agency; Business cycle; Through-the-cycle rating methodology; Method comparison

JEL classification: G20; G24; G30; G32

1 Introduction

Credit Ratings represent the opinion of a rating agency that measures the fundamental creditworthiness of an entity (i.e. a corporation) and its ability to fully and punctually meet its debt obligations (Gonzales et al. (2004)). The agencies' that

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produce these ratings are professional organisations that must comply with regulatory norms in the US and the EU (Hill (2004)). The agencies external ratings contrast to internal or so-called 'shadow ratings' that banks develop to approve loans and measure the riskiness of investments. In the case of corporations external ratings are purchased by the issuers themselves[1]. Ratings are placed on a discrete ordinal scale, where the so called 'triple A' (AAA) rating represents the highest rating assigned to issuers with the highest credit quality.

In an economic sense rating agencies function as financial intermediaries, whose existence would not be justified under the hypothesis of strictly efficient markets (Ramakrishan & Thakor (1984)). The rating market itself is mainly controlled by three agencies. These are Moody's, Standard & Poor's (S&P), and Fitch, who control around 95% of the market (Asmussen (2005), Wappenschmidt (2009), p. 13). The rating market can therefore be regarded as an oligopoly.

Issuers can use a rating as a mechanism of corporate governance to signal low investment risk and transparency (Nordberg (2010)). Ratings can in this sense reduce principal agent problems and thereby lessen a corporations capital costs (Gonzales et al. (2004)). From an investors point of view, as a highly aggregated classification of an issuers debt, ratings can inform a reader on the possibility that an issuer will not be able to meet his debt obligations (Dilly & Mählmann (2010)). The ratings can moreover be used by potential investors and banks as benchmarks and reference point for their own analysis and internal ratings (Erlenmaier (2006) p. 39).

Credit ratings and their movements are furthermore of empirical importance for several reasons. They form the basis of a large part of regulation for institutional investors (Hill (2004)). These investors can only purchase or hold bonds that have a certain quality. Rating changes have a measured effect on the price of bonds (Katz (1974)) and on stock prices (Jorion & Zhang (2007)) of a corporation. They are furthermore employed in risk modeling (Nickel et al. (2000)). In this sense rating transitions are relevant to determine the future development of the risk assessment of a given portfolio.

[1] If they are solicited. Unsolicited ratings are rare and most ratings are solicited and withdrawn at the firms request.

Rating agencies insist that they apply a through-the-cycle approach to determine the long-term credit worthiness independent of short-term business cycle effects (Amato & Furfine (2004)). Yet, at least rating transitions do vary across the business cycle (Nickel et al. (2000)). Rating transitions furthermore exhibit non-Markov effects, i.e. the probability of of a rating transition is not only dependent on the state it is in (Lando & Skødeberg (2002)). Transitions are shown to be dependent on momentum (if an up- or downgrade occurred before) and duration (how long a rating has been in a certain class) effects. These studies however do not employ firm specific risk factors (Nickel et al. (2000) and Lando & Skødeberg (2002)).

Empirical papers on credit ratings can be roughly divided into three groups. In the first group research focuses on the accuracy and predictive power of ratings. These studies measure the correlation of ratings and future defaults to examine if credit ratings present what rating agencies claim they present: a measurement of a corporation's creditworthiness. Studies by Zhou (2001) and Jorion & Zhang (2007) show that over long term observations, i.e. around 10 years, the default accuracy of ratings increases, i.e. higher rating classes have lower default frequencies, when compared to one year default frequencies. Moreover, default rates do not increase constantly. Rather the differences in default rates increase moving down the rating scale.

The second group of studies measures the information content of credit ratings and if ratings provide information which capital markets do not already incorporate. They thereby test the efficient market hypothesis by analysing the market dynamics of bond, stock, and CDS prices around rating events (for a review see Gonzales et al. (2004)). Most studies find an asymmetric reaction of markets to rating changes. Specifically, markets react stronger to downgrades than to upgrades (Jorion & Zhang (2007)).

The third line of research analyses to which degree publicly available information is reflected in the agencies' judgement, or how accurately ratings can be reproduced with public information. We find three main distinct groups of variables that determine credit ratings and credit rating changes: financial data and ratios (Ederington (1985), Blume et al. (1998), and Altman & Rijken (2004)), corporate governance characteristics (Bhojrai & Sengupta (2003), Ashbaugh-Skaife et al. (2006), Jorion et al. (2009)), and macroeconomic factors (Nickel et al. (2000) and Amato & Furfine (2004)).

Financial ratios are the basic determinants of credit ratings, as the relation of for instance leverage and credit worthiness is intuitive. Different sets of these variables are applied in most empirical applications (an exception is Nickel et al. (2000)) and are necessary control variables to test the influence of other variable groups.

Corporate governance mechanisms can influence the credit worthiness in basically two ways. First, with respect to the principal agent problem between stockholders and management (Bhojrai & Sengupta (2003)). And second, through wealth transfer effects from bondholders to shareholders (Ashbaugh-Skaife et al. (2006)). Furthermore, Jorion et al. (2009) analyse the impact of changes in accounting quality on credit ratings.

Macroeconomic factors can either be reflected in changing agency standards (Blume et al. (1998)) or through a dependence on the business cycle (Nickel et al. (2000) and Amato & Furfine (2004)). At the time of this writing no study has to our knowledge applied all three groups of variables. The only study that addresses the interaction of all three groups is Jorion et al. (2009).

A large variety of empirical methods has been applied to credit rating estimation and prediction. Ederington (1985) tests the performance of ordinary least squares (OLS), multivariate discriminate analysis (MDA), ordered probit, and unordered logit. Other studies apply machine learning methods, e.g. neuronal networks (e.g. Dutta & Shekhar (1988)). Yet, in most economic and business studies the ordered probit model has established itself as the dominant method.

The ordered probit model has two main advantages that relate to the specific character of credit ratings. It can reflect the ordinal feature of credit ratings, i.e. the difference of creditworthiness between two rating categories varies along the rating scale. Second, the probit method can assume the ordered structure of the ratings. A weakness of the ordered probit approach is that it implicitly assumes that agencies apply a point-in-time perspective to credit ratings (Altman & Rijken (2004)). Agencies however insist that they rate through-the-cycle and try to evaluate the credit worthiness independent of short-term business cycle effects. Therefore a probit approach is expected to predict more rating changes than are observed, as agencies try to achieve rating stability. To compensate for such effects some studies employ duration and hazard methods to estimate rating changes (Du & Suo (2005)).

In the spirit of Blume et al. (1998), Amato & Furfine (2004), and Jorion et al. (2009) we apply a panel ordered probit model to estimate the S&P ratings of the 100 largest US non-financial firms in 2005 in the time span from 1990 to 2009. We reexamine their results with respect to the possible increasing stringency of rating agencies standards (suggested by Blume et al. (1998)), the correlation with the business cycle (Amato & Furfine (2004)), and an alternative explanations of the findings of Blume et al. (1998) suggested by Jorion et al. (2009). Moreover, we apply an OLS regression where the ratings are transfered into default probabilities calculated by Jorion & Zhang (2007) to highlight the divergence of the through-the-cycle and point-in-time perspective found by Altman & Rijken (2004) and Altman & Rijken (2006).

The paper continues as follows: we present the rating distribution of our sample in Section 2. Section 3 presents the financial and macroeconomic explanatory variables used in this study to determine credit ratings and their sample properties. In Section 4 we discuss the statistical methods used in our study and their specific properties. The empirical results are presented and discussed in Sections 5 to 7. In Section 5 the stability of coefficients assumed in the ordered probit model is analysed. Section 6 reexamines the results of Blume et. al (1998) and Amato & Furfine (2004) with respect to the increasing stringency of rating agencies and procyclical properties of credit ratings respectively. In Section 7 we analyse the effects of the through-the-cycle approach on rating stability. Section 8 concludes.

2 Ratings

Ratings range from AAA assigned to firms with the highest debt quality to D, which is given to firms in default. Ratings from AA to CCC can furthermore have a '+' or a '-' that indicate more subtle differences in creditworthiness. Ratings from AAA to BBB- are considered investment grade ratings, while BB+ and lower ratings are called speculative ratings. The difference between BBB- and BB+ is important, as for instance institutional investors may not purchase bonds rated BB+ or lower

(Hill (2004)). For the purpose of estimation, we group all AA, A, BBB, BB, B, and CCC, CC, and D ratings together so we have $K = 7$ rating categories.

The encoding for each rating category and its 10 year default frequency calculated by Jorion & Zhang (2007) are depicted in Table 1. Noticeably, the differences in default frequencies increase down the rating scale. For instance, the difference between BBB- and BB+ of just one notch is larger than the difference from AAA to AA- of four notches.

For the purpose of this study we collect S&P foreign long term issuer ratings from 1990 to 2009[2]. The sample excludes banks and other financial firms in contrast to Blume et al. (1998) and Amato & Furfine (2004)[3]. The sample comprises the 100 largest US non financial publicly tradable stock companies of 2005.

Table 2 depicts the distribution of rating classes of our sample across time. In comparison to Amato & Furfine (2004) there are comparatively fewer lower rated firms. This could be caused by the sample selection. As seen below in Section 3 larger firms have ceteris paribus better ratings[4]. Therefore the choice of the 100 largest firms in 2005 might result in fever lower rated firms.

3 Explanatory variables

Credit ratings are determined by basically three different groups of variables. The first are financial data and ratios that measure factors such as leverage, liquidity, and profitability (see e.g. Blumen et al. (1998)). The second group covers corporate governance characteristics. Studies that employ corporate governance characteristics aim to measure the effects of corporate governance mechanisms on credit ratings that influence principal agent problems between management and stockholders (Bhojrai & Sengupta (2003)) and the redistribution of wealth from bondholders to shareholders (Ashbaugh-Skaife et al. (2006)). The third group comprises mac-

[2] Issuer and issue ratings can have different determinants. A issue rating determines the creditworthiness of one specific obligation, while the issuer rating reflects the firms creditworthiness in general.

[3] This distinction may lead to different empirical results, as financial companies have different capital structures.

[4] Jorion et al. (2009) note that in their sample on average investment firms are nine times as large as speculative firms.

roeconomic variables that measure business-cycle effects and fundamental changes. Rating agencies insist that they employ a through-the-cycle approach that estimates the long term credit worthiness of a firm independent of short term business cycle-effects. Nevertheless, credit ratings are found to correlate with the business-cycle (Amato & Furfine (2004) and Nickel et al. (2000)).

In this study we employ 10 variables extracted from financial statements that fall into the first category. Following Blume et al. (1998) we use pretax interest coverage, operating income to sales, a long term debt ratio, a total debt ratio, and total assets. Furthermore, we employ 2 ratios suggested by Altman (1968) to predict corporate bankruptcy and later used in credit rating studies by Altman & Rijken (2004) and Kim & Sohn (2008). These ratios are the retained earnings to total assets, the earnings before interest and taxes (EBIT) to total assets, and sales to total assets. The list is concluded by the return on assets ratio. For both the ROA and the total debt-total assets ratio we include a five year average.

3.1 Definitions and possible effects

Specifically, pretax interest coverage (IC) is operating income after depreciation plus interest expenses divided by interest expenses. Operating income should be positively related to ratings. More specifically, a decline in interest expenses should improve ratings if operating income after depreciation is positive. Blume et al. (1998) highlight the non-linear influence of interest coverage, i.e. for small values of interest coverage changes are relevant while for large values changes become negligible. Furthermore, negative values are not meaningful as a negative operating income and a decline in interest expenses would cause a positive development at the margin although the variable would become negative (Amato & Furfine (2004)).

The operating income to sales ratio (OI NS)is defined as operating income before depreciation divided by net sales. This ratio is a proxy of both earnings and cash flow. A firm's earnings margin indicates if it can generate the necessary cash to service its debt obligations. Moreover, the value of a firm's assets are measured by its earnings.

The long term debt ratio (LTD/TA) and the total debt ratio (TD/TA) are both measures of leverage. They are respectively defined as long term debt divided by total assets and the sum of long term debt, debt in current liabilities, and short term debt divided by total assets. Issuer ratings measure a firm's ability to serve all its financial responsibilities but are also linked to the issue rating of unsecured long-term debt. Therefore, a distinction between long-term debt and total debt seems appropriate to measure the magnitude of a firm's debt obligations (Amato & Furfine (2004)). Both ratios should be negatively related to credit ratings.

Amato & Furfine (2004) consider firm size (TA) to be a measure of business risk. Larger firms tend to be older and have more diversified product lines and a higher variety of revenues [5]. Therefore firm size should be positively related to credit ratings. Blume et al. (1998) furthermore find that financial ratios are more informative for larger firms by modelling the residual variance as a function of firm size. This result implies that variables for larger firms are more stable over time or alternatively that relevant variables are missing in their analysis[6].

In the spirit of Altman's (1968) default prediction model, Altman & Rijken (2004), and Kim & Sohn (2008) we furthermore include a retained earnings to total assets ratio (RE/TA). This ratio proxies the historic profitability of a firm, and furthermore implicitly measures the age of a firm, as older firms usually have a higher retained earnings total assets ratio. The retained earnings can be used in less profitable times to ensure the service of obligations and should therefore be positively related to credit ratings. Indeed Kim & Sohn (2008) find that the retained earnings total assets ratio is strongly related to future upgrades.

Similarly, the earnings before interests and taxes to total assets (EBIT/TA) is a proxy of the firm's current profitability (Altman & Rijken (2004)). It measures the true productivity of a firm's assets (Altman (1968)). A core element of a firm's existence including its creditworthiness is based on the earnings power of its assets. This ratio should therefore be positively related to credit ratings.

Return on assets (ROA) is a further measure of profitability. For individual firms the proxy of profitability used by the rating agency may differ. Furthermore, we include the five year arithmetic average of ROA (ROA 5yr) to test if we can thereby

[5]For similar reasons Altman & Rijken (2004) use firm age as a determinant.

[6]Firm size measured by total assets is deflated using a CPI taken from the US Department of Labour form the 2011.04.15 downloaded 2011.04.28: `ftp://ftp.bls.gov/pub/special.request/cpi/cpiai.txt` . Then the natural logarithm is taken.

capture changes in the fundamental creditworthiness of firms.

Some studies (e.g. Blume et al. (1998), Bhoiraj & Sengupta (2003), and Amato & Furfine (2004)) use market based measures of risk, i.e. the market β, as further determinant of credit ratings. Yet, as can be seen in Bhoiraj & Sengupta (2003), the measured relationship between β and credit ratings varies if different characteristics of corporate governance are used. This suggests that the effect of market based measures and credit ratings is not yet fully understood. We therefore omit these variables from our analysis.

Amato & Furfine (2004) use three measures of the business cycle in their study to test the procyclicality of credit ratings: The NBER recession indicator, the real and potential GDP output gap, and a discrete measure of that same output gap. Here, we only employ the actual GDP output gap (GDP GAP), as it is the only business cycle measure with a significant impact in Amato & Furfine (2004) study. As the GDP growth gap is positively correlated with real GDP, GDP GAP should be positively related to credit ratings[7].

3.2 Sample properties

In Table 2 The mean values of the explanatory variables are given for each rating class and the not rated firms (NR). There seem to be no apparent trends for IC and EBIT/TA. The means of OI NS increase down the rating scale. Because of this feature we might not be able to detect a positive relationship between OI NS and credit ratings, despite the fact that this is documented in other studies (e.g. Blume et al. (1998)). The TA variable shows a slight downward trend that indicates the expected positive relationship. This can be also said about ROA and ROA 5yr. Except for CCC a downward trend can also be seen in RE TA. The measures for leverage LTD/TA, TD/TA, and TD/TA 5yr appear to be U-shaped. Overall, the distributions of the explanatory variables might cause difficulties to measure significant effects.

The sample selection criteria might cause the firms to be too similar with respect

[7] The GDP output gap can be downloaded from `http:\\www.imf.org`.

to their capital structure, so that other firm specific factors may help to determine differences in creditworthiness. Macroeconomic factors must be ruled out, as they effect all firms equally. Yet, differences in corporate governance characteristics like those employed by Bhoiraj & Sengupta (2003) and Ashbaugh-Skaife et al. (2006) could be more adequate.

In Figure 1 the correlation of GDP GAP and the ratio of up- and downgrades from 1990 to 2009. Note that the ratio of up- and downgrades can not go below zero, and therefore it can not follow the GDP GAP in 2009 but converges towards zero. As in Amato & Furfine (2004) there appears to be a positive correlation of rating transitions and the business cycle.

4 Statistical methods applied

It is standard to use an ordered probit model to estimate and predict credit ratings (Blume et al. (1998), Amato & Furfine (2004)). An extensive method comparison is given by Ederington (1985). Here ordinary least squares (OLS) regression, multivariate discriminant analysis (MDA), unordered logit, and ordered probit are compared.

As mentioned above, the rating scale has specific features that can be best exploited by an ordered probit model, more specifically, an ordered probit panel approach for cross sectional time series analysis. Furthermore, ratings are also estimated with an unordered logit panel model, and using the corresponding default frequencies estimated by Jorion & Zhang (2007) in an OLS regression. The unordered logit model tests the assumption that effects are constant over all rating classes made by the ordered probit approach. The default frequency approach tests the effect of the agencies' through-the-cycle approach as it implies a stronger point-in-time perspective.

4.1 Ordered probit estimation

The ordered probit approach is the established method used in most studies measuring the determinants of credit ratings (e.g. Blume et al. (1998), Amato & Furfine

(2004), and Jorion et al. (2009)). Altman & Rijken (2004) use an ordered logit model, which does not differ much in application or result[8].

The ordered probit approach regresses the observed discrete rating categories on explanatory variables by an unobserved continuous variable that underlies the ratings. Partitioning the range of the unobserved variable then sorts it into the discrete categories. The unobserved variable is a linear function of the observed explanatory variables. We define the unobserved variable as the likelihood of not defaulting.

The ratings of firm n at the end of year t is denoted as $R_{n,t}$ and encoded as 7 for AAA till 1 for CCC+ and below. Then $y_{n,t}$ is the unobservable variable likelihood of not defaulting or creditworthiness that underlies the $R_{n,t}$, for which μ_k for $k = 1, \ldots, K-1$ are the partition points independent of n and t. The fixed effects panel model for $y_{n,t}$ is then:

$$y_{n,t} = \alpha_t + \boldsymbol{X}_{n,t}\boldsymbol{\beta}' + \epsilon_{n,t}, \tag{1}$$

where α_t is the intercept for year t, $\boldsymbol{\beta}$ is a $p \times 1$ vector of coefficients, $\boldsymbol{X}_{n,t}$ is a $1 \times p$ vector of the n-th firm's specific risk factors in year t, and $\epsilon_{n,t}$ is a Gaussian error term.

The most probable rating category for any observation given $\boldsymbol{X}_{n,t}$ is then the estimated $\hat{y}_{n,t}$:

$$Pr(R_{n,t} = k|\theta) = \begin{cases} Pr(\hat{y}_{n,t} \geq \mu_6|\theta) & \text{for} \quad k = 7 \\ Pr(\mu_k > \hat{y}_{n,t} \geq \mu_{k-1}|\theta) & \text{for} \quad k = 6, \ldots, 2 \\ Pr(\mu_1 > \hat{y}_{n,t}|\theta) & \text{for} \quad k = 1. \end{cases}$$

4.2 Unordered logit

Alternatively, Ederington (1985) suggest an unordered logit to estimate credit ratings. Both methods are able to incorporate the ordinal structure of credit ratings. They differ in the sense that the unordered logit can allow the coefficients of the variables to differ over rating classes but it disregards the ordered structure of credit

[8] See Ederington (1985) for a more detailed discussion. The logit and probit method differ in the error distribution. The probit approach assumes a Gaussian distribution while the logit assumes a logistic distribution.

ratings. The choice between ordered probit and unordered logit is one between structure and flexibility (Ederington (1985)). We can therefore use an unordered logit model to test the stability of the determinants of the coefficients. The results of Ederington (1985) do indeed suggest that coefficients vary over rating classes. Yet, the flexibility reduces the predictive power compared to an ordered approach.

The unordered logit is mostly constructed like the ordered probit with the exception that a logit estimation assumes a logistic distribution for the error terms $\epsilon_{n,t}$.

4.3 Employing default rates

Furthermore, the ratings can be translated into corresponding default rates D_k estimated by Jorion & Zhang (2007). Then, $1 - D_k$ presents the likelihood of not defaulting. Taking as unobserved variable the probit of this likelihood, we can do an OLS regression on this. We can then use the arithmetic half-way distances between the default frequencies as thresholds in order to assign the estimated likelihood of not defaulting values to credit ratings.

Using default frequencies, Jorion & Zhang (2007) could show that price-adjustment processes can be better explained if they are conditioned on the prior rating[9]. Similarly, if credit ratings behaved like other default measures that employ a more point-in-time perspective such as Merton-type methods, this approach should improve rating prediction. Yet, agencies insist that they use a through-the-cycle approach. This is motivated so as to ensure a degree of rating stability (Altman & Rijken (2006)). Therefore, the default measure approach should produce a rating transition matrix with larger transition probabilities (Altman & Rijken (2004) and Kim & Sohn (2008)). The transition frequencies of this method should therefore produce an upper bound and the actual rating transition matrix a lower bound for the purpose of model evaluation. The estimated transition probabilities of an ordered probit or an unordered logit should lie between these values.

[9]Prior research had failed to find significant price reactions after upgrades.

5 Coefficient stability

We first analyse our results with respect to the stability of the determining variables, thereby testing the underlying assumption of the ordered probit panel fixed effects model that the coefficients are constant over time and rating classes. To test the stability over rating classes we compare the ordered probit results with an unordered logit regression. Furthermore, we test the stability of the coefficients over time by performing yearly probit regressions.

5.1 Ordered probit panel

In Table 4 the results of four different ordered probit panel regressions are displayed[10]. First, they are used unmodified in the 'naive' regression. The second regression 'AV' tests if fundamental changes in creditworthiness can be captured by subtracting the current TD/TA, and ROA ratios from their respective five year averages. We then follow Blume et al. (1998) and allow IC to have a non linear effect in 'IC AV'[11]. In the last regression we only include the five year averages of TD/TA and ROA and omit their current values. This approach proxies other studies that use three year averages (Blume et al. (1998) and Amato & Furfine (2004)).

In comparison to the results of other studies both interest coverage and operating income to net sales have the opposite impact. Moreover, interest coverage has no significant effect even after allowing for non linear effects.

The three measures of leverage have no significant effect if they are all used in a regression. Yet, when we omit for instance TD/TA and its five year average, LTD/TA has the expected significant negative effect. Subtracting the current TD/TA from its five year average does not seem able to capture a fundamental change in the creditworthiness, as its coefficient is not significant nor does it have the expected negative sign. The insignificance and varying impact might be caused by multicollinearity within the variables[12].

[10] Only the coefficients of the variables are shown. The yearly constants are discussed in detail in Section 6 below.

[11] In contrast to Blume et al. (1998) we only partition IC into three variables, as there are no $IC > 20$. For more details see Blume et al. (1998).

[12] Amato & Furfine (2004) suggest this to explain the non significant effect of TD/TA in their

The impact of profitability measures that determine credit ratings depend on the set of estimators used in each regression. The most stable effect is caused by ROA, while other measures like EBIT/TA might even have a negative impact. ALtman & Rijken (2004) interpret some measures as proxies for past, present, and future profitability. Moreover, agencies might select which measure is most important in their assessment depending on the firm's circumstances. In contrast to Blume et al. (1998) measures of profitability often fail to have a significant impact. As noted in Section 3 this might be caused by small variation of the explanatory variables across rating classes compared to other studies.

Firm size measured by has a constant significant positive effect independent of further variable selection. It is also in this sample an important measure of the creditworthiness of firms.

5.2 Stability over rating classes

We next test the assumption that effects over rating classes are constant. For this purpose we analyse the results of an unordered logit panel estimation. Table 5 presents the coefficient results of this estimation[13]. Here the $K-1$ groups of coefficients determining ratings between all rating classes.

As in the ordered probit estimation interest coverage has no significant coefficients. The OI/NS and TA variables have the same stable significant effects as in the ordered probit estimations. In contrast to the probit estimations the measures for leverage have significant effects, although not for lower rating classes. Across all rating classes except for CCC to B at least one measure has a significant effect.

Except for ROA 5yr, the proxies for profitability have significant effects over almost all rating classes. The coefficients of the retained earnings ratio and ROA are both positive. The EBIT ratio has an unexpected negative effect like OI NS.

The results of Ederington (1985) indicate that coefficients might not necessarily be constant over rating classes. Yet, in studies such as Blume et al. (1998) and Jorion et al. (2009) the variables have stable significant effects. In our sample a

study.

[13]As above for the ordered probit panel estimation, we discuss the results of the constants in detail in Section 6.

functional coefficient model might solve the problem posed by the variation of effects across rating classes. Moreover Blume et al. (1998) show that financial ratios are more informative for larger firms than for smaller ones. Furthermore, Bhojrai & Sengupta (2003) find that corporate governance characteristics are have a larger effect for lower rated firms. These two findings fit neatly together, as larger firms are on average better rated. This is compatible with the results in Table 5, where there are fewer significant coefficients for lower rating classes[14]. Therefore, the factor determining the coefficients of credit rating determinants might be firm size.

5.3 Stability over time

In order to test the assumption of the fixed effects approach that coefficients are constant over time we perform yearly ordered probit regressions independent of each other. Table 6 displays the results of these estimations.

We find that except for TA almost no variable has a significant effect in any given year. This further highlights the importance of firm size in the agencies' assessment of a firm's creditworthiness. As the sample size and variation in the panel probit approach might be too small to produce significant results, the situation for a year by year analysis is even more difficult[15].

Overall, we note that the sample size and variable variation within the sample might be too small and selective to capture significant effects observed in other studies. Allowing coefficients to vary across rating classes solves this dilemma to a certain degree.

6 Macroeconomic effects

The procyclicality of credit ratings is empirically observed although rating agencies apply a through-the-cycle approach. Therefore, using a measure of the business cycle as a control variable seems appropriate, when discussing the results of Blume et al. (1998) who suggest that the decreasing constants of the fixed effects panel model indicate that agencies standards have become more stringent over time. Jorion et

[14] There are also less observations in these rating classes, which might cause this result.

[15] This finding does not change if different subsets of the variables are used.

al. (2009) argue that this effect disappears if a firm specific measure for accounting quality is used. More specifically, accounting quality of investment grade firms seems to have declined over time.

We analyse the evolution of ordered probit panel constants from the 'IC AV' model in Section 5 to compare the properties of our sample with the results of Blume et al. (1998), Amato & Furfine (2004), and Jorion et al. (2009). The development of the six groups of constants from the unordered logit estimation are shown in Section 5 and compared with the findings of Jorion et al. (2009) that the constants only had a negative trend for speculative ratings. Last, we measure the influence of a business cycle measure both for a ordered logit model and an unordered logit estimation in the spirit of Amato & Furfine (2004), who found that investment ratings were more sensitive to business cycle effects.

6.1 Yearly constants

The yearly constants of the 'naive' regression are displayed in Table 7. The dummies show a negative trend and decrease in time from zero[16], set in 1990, and become significantly negative. Figure 2 displays the evolution of the dummy variables of our sample along with the results of Blume et al. (1998), Amato & Furfine (2004), and Jorion et al. (2009). The yearly dummies show a similar trend to those of the other studies.

The sample of Blume et al. (1998) contains only investment grade ratings, while Amato & Furfine (2004) and Jorion et al. (2009) also include speculative ratings. Moreover, Jorion et al. (2009) perform two distinct estimations for investment and speculative ratings. Our yearly constants behave similar to the investment grade estimation of Jorion et al. (2009). This result can be expected as our sample contains more investment grade ratings by comparison to Amato & Furfine (2004).

Notably, Blume et al. (1998) interpreted the negative trend in the yearly dummies as evidence that agencies' standards have become more stringent. They show that the coefficients of the explanatory variables are stable over time[17]. They therefore argue that the negative trend is evidence that agencies have become more

[16]Each study sets the first year dummy to zero.

[17]This is tested using a random effects model. The main results stem from a fixed effects model.

critical in assessing the creditworthiness of firms. Furthermore, Amato & Furfine (2004) show that these results are robust to the inclusion of measures of the business cycle.

Blume et al. (1998) dismiss the critique that the trend might indicate the development of factors which were omitted from their study, by arguing that the literature did not suggest further important determinants of credit ratings at the time. Yet, since then Bhojrai & Sengupta (2003) and Ashbaugh-Skaife et al. (2006) have shown that credit ratings are also dependent on corporate governance characteristics. Nevertheless, neither study addresses a possible impact of corporate governance mechanisms on rating stability.

Jorion et al. (2009) provide an alternative interpretation to the negative trend. Rating agencies are dependent on the information provided by the firms themselves, as the agencies do not themselves collect data, their assessment is critically reliant on the quality of the firm's accounting data (Hill (2004)). Jorion et al. (2009) first show that the negative trend is restricted to investment grade ratings (see Figure 2). Furthermore, after including a measure of firm specific accounting quality the negative trend disappears. They therefore attribute the observed decline to changes in accounting quality.

In Table 8 the constants of the unordered logit estimation are displayed. Yet, contrary to the results of Jorion et al. (2009) we find no apparent negative trend for higher rating classes. Moreover, a negative trend is found for CCC to B, implying the exact opposite of the Jorion et al. (2009) results. Yet, as already mentioned our sample contains fewer lower rated firms and therefore our results might not be representative.

6.2 Procyclicality of credit ratings

We test the dependence of our sample on macroeconomic trends by including a measure of the business cycle (GDP GAP) in an ordered probit and an unordered logit estimation. Here, the yearly constants are replaced by a trend variable that is t for the respective year. With the unordered logit estimation we test the Amato & Furfine (2004) finding that investment grade firms are more sensitive to the business cycle. This finding is somewhat counterintuitive, as agencies stress that in particular the default of CCC rated firms is highly dependent on the economic situation[18]. Furthermore, Nickel et al. (2000) find that at least the transition frequencies of lower rated firms are more sensitive to the business cycle.

In Table 9 the results of the ordered probit estimation with a trend variable and GDP GAP are displayed using the 'naive' set of variables. We find that the effects and significance of firm specific variables does not change substantially in comparison to the estimation in Section 5. The trend variable has a negative effect, which can be expected given the downward trend of the yearly constants. As in Amato & Furfine (2004) the downward trend is positively related to credit ratings.

Table 10 shows the results of an equivalent unordered logit estimation. Similarly, the coefficients do not change compared to those of the estimation in Section 5. The trend has a negative impact over all rating classes. Yet, the effect of the business cycle varies. It is insignificant for investment ratings, while speculative ratings are positively related to it. This is the opposite finding of Amato & Furfine (2004), yet restricted to our subsample.

Overall, the results indicate that with respect to yearly constants and business cycle measures the sample has similar features as those of other studies using larger samples. Furthermore, an unordered logit suggests that speculative firms are more sensitive to the business cycle.

7 Rating stability

Rating stability is an objective of rating agencies along with accuracy and timeliness. The stability objective is expressed in the agencies' through-the-cycle approach (Altman & Rijken (2006)). Altman & Rijken (2006) highlight the consequences of this approach on rating transitions. Altman & Rijken (2004) and Altman & Rijken (2006) results indicate that ratings are more stable than measures from a more point-in-time perspective. Rating transitions play an important role in risk management as they reflect the riskiness of a given portfolio. In this respect the estimation and prediction of transition probabilities is highly important.

[18]See Standard & Poor's Rating Definition, www.standardandpoors.com/ratingdirect.

We compare rating transitions probabilities estimated from actual ratings in the sample with the probabilities of the ordered probit approach and the OLS estimation using default rates. Furthermore, we compare our sample results with those of Nickel et al. (2000)[19].

Nickel et al. (2000) estimate rating transitions from a Markov perspective conditioned solely on the current rating class. Other studies show that rating transitions are also dependent on non-Markov effects, i.e. duration and momentum (Lando & Skødeberg (2002) and Du & Suo (2005)). In this application we ignore possible Non-Markov effects and follow Nickel et al. (2000) using transition frequencies to estimate transition probabilities. This is appropriate as we use the estimated transition matrices to evaluate our methods with regard to rating stability.

The three transition matrices are shown in Table 11. Transition probabilities p_{ij} reflecting the probability of rating in category i in year t to change to category j in $t+1$ are estimated by dividing the sum of firms that are in rating category i in year t and transition to category j in $t+1$ by the sum of all firms in category i in year t[20].

In comparison to Nickel et al. (2000) we find that there are fewer lower rated firms in our sample. As a consequence the transition probabilities for lower rated firms are not as stable. For CCC ratings there are more transitions out of the rating class than stay in there. Consequently rating transition probabilities from the actual ratings should be considered inaccurate for this rating class.

The transition matrices designed using the ordered probit estimation and OLS regression using default rates highlight a problem that might be caused by the sample selection. There are no estimated ratings in the highest and lowest rating categories. Nevertheless, the transition probabilities of the ordered probit estimation are higher than the actual transition frequencies and lower than those estimated from the OLS regression, thus confirming the results of Altman & Rijken (2004).

This result has important implications for risk management. The risk of a portfolio needs to be interpreted differently if different measures of creditworthiness are used, in particular point-in-time measures (Merton-type models) and through-the-

[19]Nickel et al. (2000) use Moody's ratings, but nevertheless set a benchmark study.

[20]The p_{ij} in each row do not ad up to one as we omit the withdrawn ratings.

cycle (ratings).

8 Conclusion

This study analyses the statistical properties and stability of ratings from a sample made up of the 100 largest US-non-financial firms in 2005. We perform an ordered probit panel estimation, an unordered logit, and an OLS regression using default frequencies of the respective rating categories.

The sample is possibly too small and selectively chosen to find significant effects of standard explanatory variables. This is emphasised by the small variation and sometimes counter-intuitive trends in the variable distributions across rating classes. Indeed, in multiple ordered probit estimations some variables fail to have a significant effect or even have the opposite sign that other studies find. In an unordered logit estimation some of these variables are found to have a significant effect, suggesting that coefficients vary across rating classes.

The macroeconomic properties of the sample are consistent with the findings of larger studies. An unordered logit estimation suggest that lower rated firms are more sensitive to the business cycle. The transition probabilities estimated by the OLS regression using default rates highlight the through-the-cycle approach of the rating agencies. Point-in-time perspective measures tend to vary stronger over time than agencies' credit ratings.

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A Tables

Rating	D_k	$R_{n,t}$
AAA	0.005	7
AA+	0.004	6
AA	0.007	6
AA-	0.012	6
A+	0.016	5
A	0.017	5
A-	0.023	5
BBB+	0.047	4
BBB	0.055	4
BBB-	0.109	4
BB+	0.140	3
BB	0.187	3
BB-	0.265	2
B+	0.315	2
B	0.396	2
B-	0.492	2
CCC	0.572	1
Time period	1981 – 2002	

Table 1: Default frequencies of rating categories of Standard & Poor's (Source Jorion & Zhang (2007)) and classification.

Rating Distribution									
	AAA	AA	A	BBB	BB	B	CCC–CC	D	NR
1990	6	13	19	3	6	3	0	0	50
1991	6	12	21	8	6	3	0	0	44
1992	8	13	25	8	8	3	0	0	35
1993	8	13	26	8	11	1	0	0	33
1994	7	14	26	10	10	1	0	0	32
1995	7	13	28	14	10	0	0	0	28
1996	7	15	28	15	8	1	0	0	26
1997	7	16	29	20	4	1	0	0	23
1998	7	17	31	23	2	0	0	0	20
1999	8	15	31	26	6	0	0	0	14
2000	8	15	32	29	5	1	0	0	10
2001	7	14	30	33	10	1	0	0	5
2002	6	12	32	34	10	1	0	1	4
2003	6	11	32	36	10	2	0	1	2
2004	5	10	31	37	8	4	1	1	3
2005	5	9	34	34	7	5	0	3	3
2006	5	8	35	35	5	8	0	1	3
2007	5	7	35	36	4	9	0	0	4
2008	5	8	34	33	7	6	3	0	4
2009	3	10	32	32	9	6	0	3	5

Table 2: Distribution of US sample ratings 1990 – 2009.

	Variables									
	IC	OI/NS	LTD/TA	TD/TA	TD/TA 5yr	TA	RE/TA	EBIT/TA	ROA	ROA 5yr
AAA	1.1853	0.1011	0.2483	0.3160	0.3074	23.1965	0.2808	0.0887	6.4585	6.2764
AA	1.3588	0.1322	0.2397	0.2991	0.2711	25.0726	0.2783	0.1171	7.3314	7.1281
A	1.2561	0.1112	0.1862	0.2409	0.2379	23.1174	0.3138	0.1175	7.8556	7.7337
BBB	0.3619	0.1302	0.1990	0.2564	0.2449	22.5804	0.2909	0.1135	7.7531	7.9249
BB	1.4013	0.1196	0.2452	0.3007	0.2909	22.5392	0.2704	0.1043	6.6365	6.6920
B	1.4320	0.1121	0.2787	0.3332	0.3563	22.6297	0.1400	0.0697	4.5157	4.3190
CCC	1.9840	0.1406	0.3251	0.4427	0.4153	22.9782	0.5122	0.1130	7.2933	6.5033
D	0.5523	0.0958	0.2888	0.3137	0.3178	21.8738	0.2373	0.0741	3.4144	4.6422
NR	1.7221	0.1247	0.2044	0.2554	0.2224	23.7910	0.2435	0.1378	9.2540	8.9572

Table 3: Distribution of US sample variables means conditioned on rating class.

	Naive			AV			IC AV			5yr		
	Coefficient	t-stat	P-Value	Coefficient	t-stat	P-Value	Coefficient	t-stat	P-Value	Coefficient	t-stat	P-Value
IC	-0.0566	-0.9791	0.3275	-0.0734	-1.2778	0.2013						
IC1							-0.0873	-1.1259	0.2602	-0.0637	-0.8213	0.4115
IC2							-0.0213	-0.1508	0.8801	-0.0399	-0.2837	0.7766
IC3							0.0002	0.0008	0.9994	0.0211	0.1128	0.9102
OI/NS	-2.2211	-5.1111	0.0000	-2.1473	-5.0886	0.0000	-2.1756	-5.1246	0.0000	-2.2591	-5.1746	0.0000
LTD/TA	0.4006	0.8088	0.4186	-0.7036	-2.6434	0.0082	-0.6870	-2.5358	0.0112			
TD/TA	-0.6662	-1.1061	0.2687									
TD/TA5yr	-0.5193	-0.9271	0.3539							-0.8048	-3.1382	0.0017
TD/TA-TD/TA5yr				0.1762	0.3369	0.7362	0.1703	0.3247	0.7454			
TA	0.2805	8.6251	0.0000	0.2590	8.2310	0.0000	0.2604	8.2331	0.0000	0.2758	8.6506	0.0000
RE/TA	0.1974	1.3394	0.1804	0.2736	1.9782	0.0479	0.2673	1.9299	0.0536	0.1994	1.3608	0.1736
EBIT/TA	-1.4690	-1.5522	0.1206	-0.3628	-0.5575	0.5772	-0.3707	-0.5677	0.5702	-0.0439	-0.0829	0.9340
ROA	1.8281	1.7352	0.0827									
ROA5yr	-0.1588	-0.1553	0.8766						0.0293	0.0295	0.9765	
ROA-ROA5yr				0.6293	0.7997	0.4239	0.6313	0.7985	0.4246			

Table 4: Coefficients of ordered probit panel regressions with fixed effects.

Unordered Logit Regression						
	CCC to B	B to BB	BB to BBB	BBB to A	A to AA	AA to AAA
IC	0.0823	0.0566	-0.1655	-0.2548	0.0389	0.0113
(P-Value)	(0.8715)	(0.8467)	(0.4847)	(0.1985)	(0.8358)	(0.9609)
OI/NS	-12.8299	-10.1826	-10.2069	-9.8713	-3.8397	-9.3131
(P-Value)	(0.0209)	(0.0004)	(0.0000)	(0.0000)	(0.0507)	(0.0000)
LTD/TA	-0.3333	3.5859	5.5244	8.1619	7.4600	4.4874
(P-Value)	(0.9555)	(0.3084)	(0.0379)	(0.0004)	(0.0008)	(0.0773)
TD/TA	-7.2242	2.4354	-5.8698	-9.6921	-6.8820	-5.1386
(P-Value)	(0.3563)	(0.5633)	(0.0639)	(0.0003)	(0.0076)	(0.0783)
TD/TA 5yr	2.6164	-6.8704	2.2258	5.8078	4.3859	5.8671
(P-Value)	(0.6953)	(0.0660)	(0.4355)	(0.0170)	(0.0632)	(0.0265)
TA	1.5901	0.9735	1.3536	1.2032	0.8198	0.8593
(P-Value)	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RE/TA	0.0893	3.1275	2.4272	3.4240	3.3722	2.9333
(P-Value)	(0.9543)	(0.0022)	(0.0081)	(0.0000)	(0.0000)	(0.0005)
EBIT/TA	-28.5914	-9.1570	-14.4826	-15.8840	-16.5548	-16.5900
(P-Value)	(0.0070)	(0.1026)	(0.0018)	(0.0000)	(0.0000)	(0.0001)
ROA	32.5919	12.9980	17.4583	18.4062	18.7548	19.8828
(P-Value)	(0.0017)	(0.0446)	(0.0013)	(0.0001)	(0.0000)	(0.0001)
ROA 5yr	13.0370	1.2359	-2.2200	-7.6235	-9.7167	-0.4913
(P-Value)	(0.3216)	(0.8624)	(0.7061)	(0.1303)	(0.0494)	(0.9266)

Table 5: Unordered Logit estimation.

	IC	OI/NS	LTD/TA	TD/TA	TD/TA 5yr	TA	RE/TA	EBIT/TA	ROA	ROA 5yr
1990	0.1608	0.6072	6.9468*	4.3374	−14.9474**	0.2399***	-0.6997	−26.9799**	39.5665**	-13.7125
1991	-0.2927	-1.2464	5.8923*	11.3070***	−19.8962***	0.2753***	-2.0751	−17.0913*	23.7799**	-4.4443
1992	0.3366	−5.4409**	-1.6045	8.2542*	-5.2809	0.1202**	0.4529	-6.5174	15.3128***	-1.0592
1993	-0.1079	-3.4797	0.3864	5.0907	-0.6926	0.0933*	0.5542	−16.8203***	16.1275***	12.6864**
1994	-0.2854	−4.5197**	0.7888	1.1777	1.3939	0.1308**	1.4055	-5.5590	-5.4883	12.1682*
1995	-0.0898	-0.7704	-0.8446	-1.7498	3.7124	0.1527**	0.7406	-6.3322	1.8594	5.7159
1996	1.4829***	-2.2875	-1.5309	-0.7691	1.0512	0.0934*	0.8353	2.6043	-4.8373	2.2711
1997	0.9034	−4.5205*	-3.2000	-0.7441	2.2256	0.1177*	0.6429	2.0603	-6.7408	6.5686
998	0.1709	-3.1890	1.0601	-3.2249	-0.5488	0.2871***	0.4381	−10.6923*	6.6906	-0.3445
1999	-1.5257	−5.6166**	1.2479	2.0884	-3.2302	0.4076***	-0.3400	-1.9330	7.4121	-4.4023
2000	-0.1111	−3.3526*	-1.0527	-1.6912	1.7338	0.1847***	0.0169	3.6226	3.3897	−7.6603**
2001	-0.0632	-0.9787	0.5126	-0.9969	-0.7114	0.1798***	0.3928	2.8919	1.4980	-6.7577
2002	-0.0531	-0.7807	-0.3466	1.2413	-1.7049	0.1372***	0.2145	-0.5933	-0.9467	1.4293
2003	-0.1688	-1.8914	-1.4309	1.8956	-1.2507	0.1457***	0.1491	−10.0352**	18.7320***	-3.6095
2004	0.0063	-1.6252	0.5931	-2.8567	1.6728	0.1138***	0.0328	-0.4775	0.4511	2.4794
2005	-0.0091	-0.1508	-1.7878	-3.8304	3.8681	0.1113***	0.4458	3.9373	-7.1050	0.5115
2006	-0.0230	-0.2832	-3.0970	-2.8651	3.5231	0.1263***	0.2787	3.4712	-5.4682	0.5635
2007	-0.3418	-0.8143	-1.5163	2.1594	-2.5501	0.1685***	0.5030	-1.0155	-2.5789	0.7517
2008	-0.1234	0.1988	-0.6154	2.6902	-4.2665	0.1375***	0.1783	-3.1356	3.2102	-2.6554
2009	-0.0191	0.1766	-3.8709	3.2280	-3.1277	0.1519***	-0.0334	-0.7325	0.0181	-3.3973

Table 6: Coefficients of year by year regressions. Coefficients significant at the 10% *, at the 5% with **, and at 1% level with ***.

Year dummies			
	Value	t-stat	P-Value
1990	0	-	-
1991	-0.2677	-1.1414	0.2537
1992	-0.1891	-0.8303	0.4064
1993	-0.1953	-0.8718	0.3833
1994	-0.2065	-0.9299	0.3524
1995	-0.2614	-1.1913	0.2335
1996	-0.3148	-1.4395	0.1500
1997	-0.2802	-1.3039	0.1923
1998	-0.2485	-1.1639	0.2445
1999	-0.4049	-1.9047	0.0568
2000	-0.4866	-2.3170	0.0205
2001	-0.7312	-3.4911	0.0005
2002	-0.8019	-3.8150	0.0001
2003	-0.9083	-4.3047	0.0000
2004	-1.0138	-4.7606	0.0000
2005	-1.0481	-4.8924	0.0000
2006	-1.0492	-4.8919	0.0000
2007	-1.0645	-4.9584	0.0000
2008	-1.0677	-4.9953	0.0000
2009	-1.1993	-5.5041	0.0000

Table 7: Year dummies of the ‘naive’ probit panel estimation from 1990 – 2009, where 1990 is set to zero.

	Year dummies					
	CCC to B	B to BB	BB to BBB	BBB to A	A to AA	AA to AAA
1991	-0.8468	-0.4262	-0.2824	-1.3297	-0.1430	0.0729
1992	0.3841	0.5214	-0.1815	-0.9011	0.0835	0.6108
1993	1.2416	1.0543	-0.7682	-1.1320	-0.4507	0.1786
1994	-1.5971	1.2979	-0.8039	-1.4907	-0.5857	-0.1449
1995	-1.6026	18.5677	-0.9276	-2.1042	-0.7323	-0.1552
1995	-2.4106	1.0642	-0.8585	-2.3668	-0.9284	-0.3153
1997	-2.3791	0.8809	-0.4532	-2.5066	-0.8947	-0.4035
1998	-2.9691	17.9993	0.0307	-2.7648	-1.0473	-0.7623
1999	-3.3107	17.5809	-1.1586	-3.0932	-1.1604	-0.8601
2000	-3.5395	0.2622	-1.0928	-3.1762	-1.0581	-0.7214
2001	-3.8885	-0.3507	-2.4290	-3.9264	-1.5412	-1.2567
2002	-21.1118	-0.4289	-2.5937	-4.1669	-1.8275	-1.1612
2003	-21.7130	-1.1403	-2.8907	-4.5767	-2.1102	-1.3213
2004	-22.6225	-1.9319	-2.9231	-4.8310	-2.3100	-1.4053
2005	-23.4686	-1.8635	-2.8424	-4.8163	-2.4388	-1.2841
2006	-22.5297	-2.8033	-2.5033	-5.0326	-2.5929	-1.4514
2007	-5.3292	-3.1067	-2.2894	-5.0279	-2.6160	-1.3363
2008	-23.0149	-3.1024	-2.7721	-4.7915	-2.5191	-1.3976
2009	-24.3328	-4.1453	-4.2540	-6.1777	-3.6652	-2.9052

Table 8: Yearly dummies of the unordered Logit estimation with the 'naive' variables.

Probit with macroeconomic factors		
	Coefficient	p-value
IC	-0.0561	0.3277
OI/NS	-2.1440	0.0000
LTD/TA	0.3474	0.4809
TD/TA	-0.3562	0.5437
TD/TA 5yr	-0.7788	0.1537
TA	0.2714	0.0000
RE/TA	0.1886	0.1993
EBIT/TA	-1.4653	0.1184
ROA	1.8721	0.0711
ROA 5yr	-0.1720	0.8637
GDP GAP	0.0268	0.0881
Trend	-0.0630	0.0000

Table 9: Ordered probit estimation with macro economic factors.

	CCC to B	B to BB	BB to BBB	BBB to A	A to AA	AA to AAA
IC	0.2149	-0.0589	-0.1138	-0.2039	0.0413	0.0112
(P-Value)	(0.6741)	(0.8377)	(0.6315)	(0.2861)	(0.8248)	(0.9611)
OI/NS	-10.4070	-10.4479	-9.7724	-9.5846	-3.8537	-9.0916
(P-Value)	(0.0487)	(0.0003)	(0.0000)	(0.0000)	(0.0478)	(0.0000)
LTD/TA	-0.7915	3.2867	5.2405	7.8009	7.3421	4.2447
(P-Value)	(0.8943)	(0.3453)	(0.0466)	(0.0006)	(0.0009)	(0.0909)
TD/TA	-3.9357	1.6725	-5.4527	-9.1201	-6.8234	-5.5397
(P-Value)	(0.5899)	(0.6763)	(0.0775)	(0.0005)	(0.0072)	(0.0538)
TD/TA 5yr	0.0200	-5.5717	1.9897	5.5283	4.5220	6.4449
(P-Value)	(0.9974)	(0.1042)	(0.4725)	(0.0201)	(0.0505)	(0.0128)
TA	1.4031	1.0019	1.3097	1.1694	0.8081	0.8480
(P-Value)	(0.0020)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RE/TA	0.0728	3.0050	2.5079	3.4723	3.3711	2.9812
(P-Value)	(0.9626)	(0.0034)	(0.0055)	(0.0000)	(0.0000)	(0.0004)
EBIT/TA	-25.7464	-8.1922	-14.2694	-15.5789	-16.5014	-16.0135
(P-Value)	(0.0095)	(0.1446)	(0.0018)	(0.0000)	(0.0000)	(0.0001)
ROA	30.3274	12.1664	17.3162	18.0119	18.1659	18.8900
(P-Value)	(0.0035)	(0.0529)	(0.0011)	(0.0001)	(0.0001)	(0.0001)
ROA 5yr	11.8043	1.2037	-2.4726	-7.5693	-8.8605	-0.5576
(P-Value)	(0.3068)	(0.8623)	(0.6611)	(0.1173)	(0.0613)	(0.9136)
GDP GAP	-0.0049	0.1931	0.1833	0.0352	0.0830	0.0552
(P-Value)	(0.9775)	(0.0508)	(0.0265)	(0.6190)	(0.2287)	(0.4802)
Trend	-0.5486	-0.2754	-0.1789	-0.2673	-0.1686	-0.1224
(P-Value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)

Table 10: Unordered logit estimation with macro economic factors.

	Actual rating transitions							Ordered probit estimation							OLS regression with default rates						
	AAA	AA	A	BBB	BB	B	CCC	AAA	AA	A	BBB	BB	B	CCC	AAA	AA	A	BBB	BB	B	CCCC
AAA	0.9292	0.0619	0.0088	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
AA	0.0053	0.9091	0.0749	0	0	0	0	0	0.5000	0.5000	0	0	0	0	-	-	-	-	-	-	-
A	0	0.0040	0.9194	0.0645	0.0020	0	0	0	0.0029	0.9170	0.0714	0	0	0	0	0	0.3000	0.6500	0.0500	0	0
BBB	0	0	0.0370	0.9012	0.0494	0	0	0	0	0.0917	0.8930	0	0	0	0	0	0.0067	0.7941	0.1911	0	0
BB	0	0	0	0.1653	0.7355	0.0744	0.0248	-	-	-	-	-	-	-	0	0	0.0016	0.1244	0.8576	0.0033	0
B	0	0	0	0	0.1111	0.8000	0.0667	-	-	-	-	-	-	-	0	0	0	0	0.3333	0.6667	0
CCC	0	0	0	0	0	0.3000	0.6000	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 11: Transition matrices from the actual data, the ordered probit panel estimation, and the OLS regression using default frequencies.

B Figures

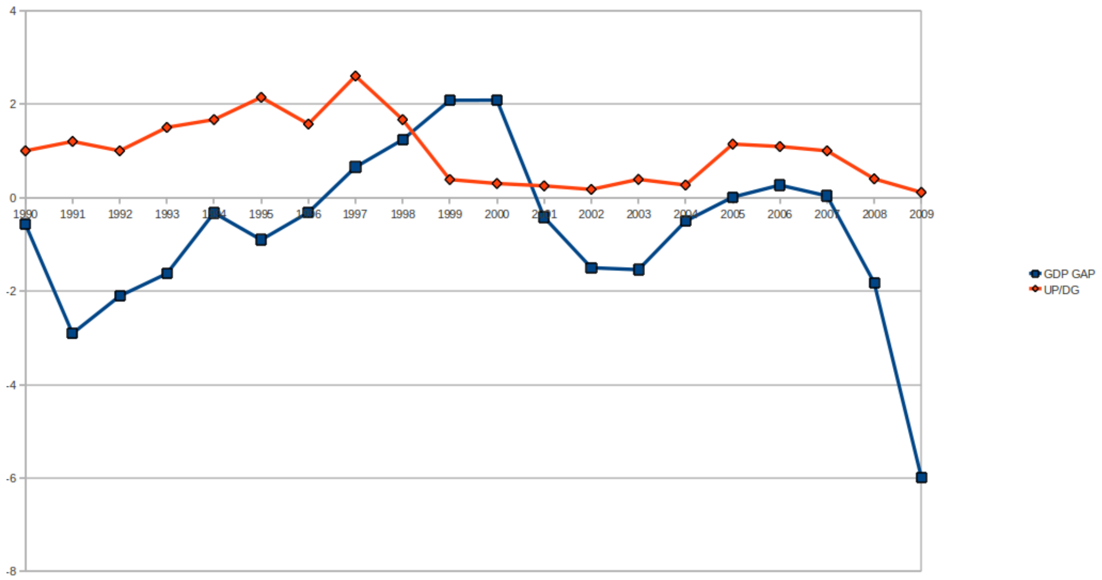

Figure 1: Correlation of the real GDP output gap and the ratio of up- and down grades in this sample.

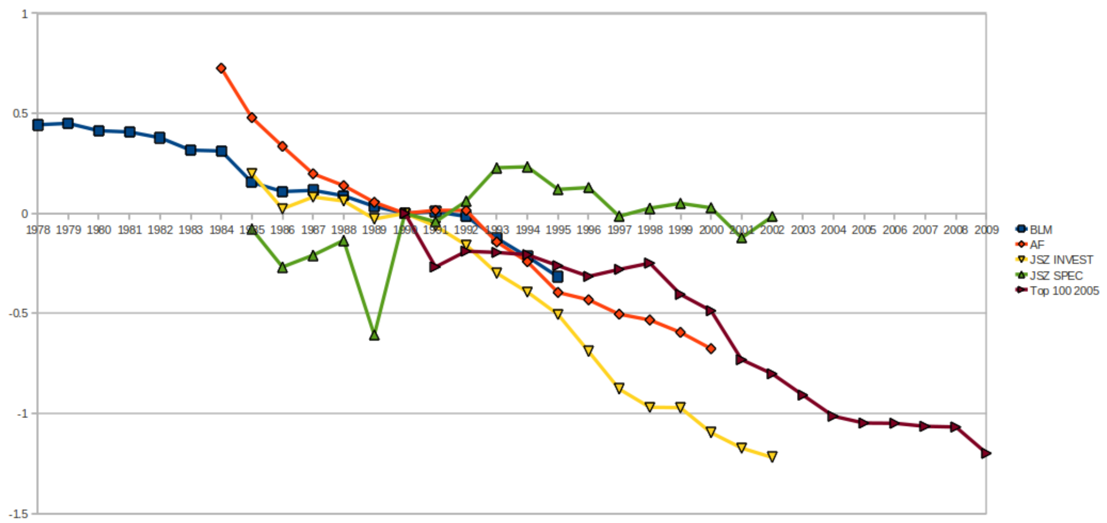

Figure 2: Evolution of probit constants over time from different studies. BLM: Blume et al. (1998), AF: Amato & Furfine (2004), JSZ INVEST: Probit regression for investment grade ratings of Jorion et al. (2009), JSZ SPEC: Probit regression for speculative grade ratings of Jorion et al. (2009), and TOP 100 2005: The sample in this study.

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