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# The Adjustment of Credit Ratings of Defaulted Issuers

**No. 155**
**April 2005**

WORKING PAPER SERIES: FINANCE & ACCOUNTING

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**April 2005**

**ISSN 1434-3401**

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We thank Patrick Behr, Gunter Löffler, Lars Norden, Paulo Rodrigues, Daniel Roesch, seminar participants in Frankfurt, Mannheim, Ulm, participants in the HVB doctoral seminar in Eltville and in the annual meeting of the Swiss Finance Association in Zürich for helpful comments. All errors and opinions expressed in this paper are of course our own.

## Abstract

We provide insights into determinants of the rating level of 371 issuers which defaulted in the years 1999 to 2003, and into the leader-follower relationship between Moody's and S&P. The evidence for the rating level suggests that Moody's assigns lower ratings than S&P for all observed periods before the default event. Furthermore, we observe two-way Granger causality, which signifies information flow between the two rating agencies. Since lagged rating changes influence the magnitude of the agencies' own rating changes it would appear that the two rating agencies apply a policy of taking a severe downgrade through several mild downgrades. Further, our analysis of rating changes shows that issuers with headquarters in the US are less sharply downgraded than non-US issuers. For rating changes by Moody's we also find that larger issuers seem to be downgraded less severely than smaller issuers.



*Key words*: rating agencies, validation, leader-follower analysis, Granger causality

*JEL Classification*: G15, G23, G33

# 1 Introduction

Credit ratings are becoming more and more important now that Basel II has come into force. Thanks to the widened application of credit ratings, the performance of rating systems will be more crucial than ever before. Since the number of internal ratings profoundly exceeds the number of external ratings, commercial banks' internal rating systems deserve particular attention. More than ever, the analysis of defaulted debtors will be an integral part of the measurement of the performance of internal rating systems. Banking regulation authorities will in future conduct in-depth analysis of the rating changes over time of debtors that subsequently default, given that these mostly non-investment grade debtors affect the regulatory equity of banks to a large degree. Since regulators have access to the rating and default data of internal rating systems, they are able to conduct leader-follower analysis for the comparison of different internal rating systems. If external rating agencies' rating levels for different periods before default are available - and we deliver them in this study - they might act as a proxy measure of how early internal ratings should be adjusted, i.e. how long before their debtors default. Since internal ratings are mostly point-in-time ratings, their adjustment process should be faster than that of external ratings, and external ratings should define the lower bound only. Besides regulation authorities, a group of cooperating banks should also be interested in performing this kind of analysis in order to detect weaker rating systems within the group, assuming that they are able to pool their internal rating and default data.

Unfortunately, performing leader-follower analysis with banks' internal data is difficult, because banks are normally not interested in sharing their data. Therefore, the rating and default data provided by external rating agencies are a possible alternative. An analysis of leader-follower relationships between external rating agencies sheds more light on the increasingly important market for external credit ratings, which should be more transparent than it is nowadays. Besides benchmark analysis of the quality of default predictions by credit rating agencies (e.g., Güttler, forthcoming), a leader-follower analysis is a further possible means of benchmarking their performance. This makes sense, since the rating leader reveals more information than rating followers. Publishing leader-follower results, ideally on a continuous basis, could allow investors and regulators to learn more about the performance of these risk assessments. This might raise the level of competition among the existing rating agencies, thereby increasing the effort exerted by the rating agencies to analyze issuers carefully.

What would be the consequences, i.e., the economically important outcome, of a leader-follower analysis? In the case of banks' internal rating systems, rating leaders will define the best practice whereas rating followers might be forced by regulation authorities to increase their efforts to install a state-of-the-art rating system. In the case of rating agencies, rating leaders should be privileged in every process of recognition by the regulation authorities, should such a process become necessary. Rating leaders should also be able to strengthen their market position in comparison to rating followers.

Since we have no access to banks' internal data we use a dataset of 371 defaulted issuers with rating and default information to analyze the adjustments of external credit ratings by the two rating agencies Moody's and S&P. As far as we know, our study is the first analysis of defaulted debtors with ratings by more than one rater.

Hence, we address two main research questions:

1) What are the determinants of the rating level assigned to debtors that will subsequently default?
2) Does one rating agency anticipate upcoming defaults earlier than the other?

The evidence suggests that Moody's assigns lower ratings than S&P for all observed periods before the default event. Besides, larger issuers and fallen angels have higher ratings and issuers belonging to the telecommunications sector have lower ratings. Furthermore, we observe two-way Granger causality, which signifies information flow between the two rating agencies. Since lagged rating changes influence the magnitude of the agencies' own rating changes it would appear that the two rating agencies apply a policy of taking a severe downgrade through several mild downgrades. Further, our analysis of rating changes by Moody's and S&P shows that issuers with headquarters in the US are less sharply downgraded than non-US issuers. For rating changes by Moody's we also find that larger issuers seem to be downgraded less severely than smaller issuers. These results should be of interest for banks, for banking regulation authorities, for the regulation authorities that oversee credit rating agencies, for the rating agencies themselves and for investors.

The study is organized as follows. Section 2 gives a brief overview of the relevant literature. This is followed by the formulation of our hypotheses. We then describe the dataset and present the empirical results. The final section contains a brief summary of our findings.

# 2 Overview of the Literature

Credit ratings have long been of interest to academic researchers. For our purpose, the literature can be divided into three relevant areas:

1) comparisons of different credit rating agencies in respect of the quality and/or timeliness of their credit ratings;
2) comparisons of the speed of adjustment of external ratings with market based measures of credit risk and that of banks' internal ratings;
3) potential reasons for the staleness of external credit ratings.

In the first area, Krämer and Güttler (2003) and Güttler (forthcoming) find that rating agencies provide profound information about the default risk of issuers in the long term. The authors compare credit ratings by Moody's and S&P on the basis of several validation measures and both come to the conclusion that Moody's seems to outperform S&P slightly. Johnson (2003) examines rating changes around the investment grade boundary. He finds that the credit rating agency Egan-Jones* leads S&P in downgrading issuers from BBB- (see table 3 for S&P's rating scale) to non-investment grade ratings.

Regarding the adjustment speed, Hand et al. (1992) and Carey and Hrycay (2001) find that credit rating agencies react relatively slowly to increasing default risk in the short term. They provide evidence that credit ratings by external agencies are relatively stable compared to alternative rating systems such as the internal rating systems employed by banks. Norden and Weber (2004) reveal that roughly 60% of the negative abnormal returns of credit default swaps due to rating downgrades take place before the rating changes have been announced. The slow reaction of external ratings to new information is also shown by Delianedis and Geske (1999). They use risk neutral probabilities of default to predict upcoming rating changes. Hence, they are able to detect rating migrations months in advance. This appears to be a clear sign that the market reacts much more quickly than credit rating agencies.

Third, the slow adjustment of external credit ratings to the changing default risk is mainly due to the "through-the-cycle" approach of the credit rating agencies, i.e. their policy of changing a credit rating only when it is unlikely to be reversed shortly afterwards (Cantor, 2001). Therefore, no credit rating change takes place if the financial situation of a company is only worsening because of a (temporary) deterioration of the general economic situation, e.g. in a recession. Löffler (2004) shows that one of the underlying reasons for the through-the-cycle approach is the desire to minimize avoidable transaction costs for institutional investors. In a more critical view of the rating industry, Amato and Furfine (2004) argue that since monitoring is costly, rating agencies may not have sufficient resources to examine all rated firms on a continuous basis. This could lead to staleness in ratings, meaning that the link between the rating of any given firm at any point in time and the factors that influence its determination might not truly reflect the decision-making behavior of the rating agency.

* Egan-Jones Ratings is a small, young credit rating agency, which has issued ratings since 1995. In contrast to S&P, Moody's, Fitch Ratings, Dominion Bond Rating Service (DBRS) and A.M. Best it is not recognized as a Nationally Recognized Statistical Rating Organization (NRSRO) by the Securities and Exchange Commission (SEC).

Our research expands the existing literature insofar as we analyze leader-follower relationships directly through Granger analysis instead of relying on (indirect) event study approaches, as Norden and Weber (2004) do. Since rating leadership is an indicator of the forecasting quality of a rater, we enlarge upon the comparison of the performance of external rating agencies offered by Krämer and Güttler (2003) and Güttler (forthcoming). Besides, our concentration on issuers that subsequently defaulted allows us to focus on the most important part of the investment universe, since this fraction is the most important one for the regulatory capital of banks and for the reputation of credit rating agencies.

## 3 Hypotheses

Since we are interested in the determinants of the rating level[†] of issuers that subsequently default, we posit the following four hypotheses:

*H1 (anticipation problem hypothesis): Companies which defaulted because of a chapter 11 filing have a better[‡] credit rating.*

We assume that defaults after chapter 11 filings are more difficult for credit rating agencies to detect than default reasons such as "missed interest payment" and "suspension of payments". This expectation is based on anecdotal evidence from public auditing firms, which gave a clean bill of health to 42.1% of the public companies that subsequently defaulted because of a chapter 11 filing between January 1, 2001 and June 30, 2002 (Weiss, 2002). This ratio seems rather high, but the lack of econometrically robust results limits the scope for interpretation of this evidence. One would expect a missed interest payment or a suspension of payments to be due to a liquidity shortage. As liquidity is one of the most important quantitative parameters

[†] We also use the four hypotheses for the analysis of rating changes. Rather than the absolute levels of the ratings, it is the magnitude of the changes in the ratings that is of interest.
[‡] In the following we use the term "better rating" to refer to a lower risk assessment by rating agencies.

in credit ratings (e.g., Standard & Poor's, 2003) a low level of liquidity is incorporated into the credit ratings. In contrast, a filing for chapter 11 is often the course of action chosen to protect a company before a problematic liquidity situation develops, and might therefore be more difficult to anticipate.[§]

*H2 (home bias hypothesis): US issuers have a better credit rating before default.*

We expect that, on average, US issuers are rated higher, or are downgraded to a lesser extent, than non-US issuers. Beattie and Searle (1992) report that rating agencies judge issuers from their own country less strictly. Shin and Moore (2003) find that ratings assigned by Moody's and S&P to Japanese firms are systematically lower than those assigned by the Japanese rating agencies R&I and JCR. In addition, Nickell et al. (2000) observe that higher rated Japanese firms are more likely to be downgraded by credit rating agencies with headquarters in the US, and Japanese firms with low ratings are less likely than US firms to be upgraded by those agencies. All these results might be explained by the conservatism of US credit rating agencies in less known markets. However, Ammer and Packer (2000) find no evidence for different default rates between US and foreign firms for the period 1983 to 1998 after controlling for time and rating effects. In our opinion, this result of Ammer and Packer (2000) might be due to the low number of defaults among foreign firms. Since they analyze 20 foreign non-financial firms, in contrast to 440 US non-financial firms, the rejection of the null hypothesis of inequality of US and foreign default rates is quite unlikely.

*H3 (incentive problem hypothesis): Larger companies have a better credit rating before default.*

We use the outstanding value of debt at the time of default as a proxy for company size. Since credit rating agencies are partly paid in basis points of the debt volume there might be an in-

[§] This differentiation is somewhat biased since chapter 11 filings (or comparable options) are not installed in all national insolvency regimes.

centive to rate bigger companies higher in order to avoid losing the client because of a pessimistic rating. Given the high degree to which the terms and conditions of borrowing are dependent on external credit ratings, downgrades are very costly for companies. It is well known that credit rating agencies rely heavily on their reputation for not allowing such considerations to influence their assessments (Covitz and Harrison, 2003). However, given the low level of competitive pressure in the credit rating market, which is dominated by only three credit rating agencies (Moody's, S&P and to some extent Fitch), there might be some incentive for moral hazard (White, 2002).

*H4 (information flow hypothesis): Changes in the credit rating by one credit rating agency increase the probability of a credit rating change in the same direction by the other credit rating agency.*

The fourth hypothesis covers the leader-follower relationship between the rating behavior of Moody's and that of S&P. Producing credit ratings is very expensive given the vast importance of soft rating criteria,[**] which must be collected through intensive contact with the management. Therefore, it would seem rational for credit rating agencies to treat rating changes by another important rating agency as a trigger prompting them to review their own ratings. Hence following the rating changes of competitors is less costly than doing one's own research. For example, Norden and Weber (2004) show that Fitch appears to follow the rating actions of Moody's and S&P to some extent. Since our research is the first known study in this area we have no clear indication of whether Moody's or S&P leads the other rating agency. Nonetheless, several empirical studies (Cantor and Packer, 1997; Ederington and Yawitz, 1987; Güttler, forthcoming; and Perry, 1985) of split ratings of issuers rated by Moody's and S&P show that Moody's assigns lower ratings on average. The ratios of split ratings, where Moody's assigns the lower rating, are between 54.44% and 62.25% in these

[**] Soft rating criteria are, for example, the quality of the management or the product policy of the issuer in comparison to its competitors.

studies.[††] Therefore, we should expect that Moody's has the leading position, because more conservative ratings should be an advantage for a sample of issuers that subsequently defaulted.

## 4 Dataset

Since we want to examine changes in the rating of companies that subsequently defaulted, a database of defaulted firms and their credit rating history before the default event is required. For this purpose, we use the default data contained in annual default reports by Moody's and S&P on publicly traded companies for the years 1999 to 2003. We define the default event as the earliest date reported by the two agencies, on a daily basis. In 19 (5.12%) cases, the default reports contained only monthly default data. Therefore, we convert these monthly data into daily data using the first day of the month as a conservative proxy for the default date. Beginning in 1990, the rating history of long-term, senior unsecured ratings, i.e. issuer ratings, and the history of so-called Watchlist entries was obtained from Bloomberg. The main advantage of this data source is that it allows the company names to be matched automatically between the datasets of Moody's and S&P.

We undertake the following sample adjustments: The raw data includes 532 default announcements by Moody's and 642 by S&P. For 404 companies, default announcements by both Moody's and S&P are observed. Excluding firms without a long-term, senior unsecured rating by both agencies before the defined default date narrows our sample down to 371 firms. This is done to avoid biased results attributable to differences between the samples of the two credit rating agencies, and to conduct a leader-follower analysis. For these 371 issuers the dataset contains 1,345 issuer ratings by Moody's and 1,789 by S&P.

[††] The reasons for these results are not clear. They could be due to the fact that Moody's applies a so-called expected loss rating approach, because not only the probability of default but also the loss given default is taken into account in the rating process, whereas S&P relies solely on the probability of default.

The annual default reports of the two rating agencies provide additional information about the reason for default, the country in which the firm's headquarters are located, the outstanding debt amount at the time of default and the line of business of the defaulted firms. An overview of these descriptive statistics is given in table 1. As debt amount, we use the reported values in billions of US dollars. If there are discrepancies between the two agencies we calculate the mean between Moody's and S&P if they report the same default date; if they do not report the same date we use the debt amount as of the earlier default date.

Missed interest payments are the main reason for default, followed by chapter 11 filings. As in other international studies, US-based firms dominate our sample, accounting for almost 80% of the total number of firms. This is due to the US origin of these two rating agencies, which did not begin to expand their activities to other regions until the 1980s. The relatively large number of defaults in Argentina can partly be explained by the sovereign default in 2001. Aside from widely known companies like Enron and Worldcom, defaults by smaller issuers dominate our dataset: in over 55.5% of all default cases, the outstanding amount of debt at the time of default is less than USD 250 million. The telecommunications sector leads by a long way, reflecting the bursting of the asset bubble and the unwillingness of investors to support these (mostly) highly leveraged companies any longer. There are 30 so-called fallen angels in our sample. These are companies which formerly had an investment grade rating (Baa3 / BBB- or better) but were downgraded to non-investment grade (Ba1 / BB+ or worse) during our observation period, which begins in 1990.[‡‡]

The five-year period for which we compile default data, 1999 to 2003, includes years in which the economy was healthy and others in which economic conditions were unfavorable. As we can see from table 2, whereas only 34 multiple defaults are observed in 1999, this variable peaks in 2001 at 117 and declines to 46 in 2003. The mean (median) amount of out-

[‡‡] Obviously, we are not able to identify as fallen angels those issuers that have a rating history that goes back further than 1990. Fallen angel status should therefore be interpreted as being applicable in the medium term only.

standing debt peaks one year later in 2002, with an average amount of USD 1.05 (0.30) billion.

To compare the timeliness of the rating adjustment by Moody's and S&P it is necessary to construct a master scale of credit ratings because the two rating agencies do not apply the same rating scale, even though their rating scales look quite similar at first sight. Furthermore, Moody's assesses the probability of default (PD) and the loss given default (LGD), whereas S&P only evaluates the PD (Estrella, 2000). Our mapping approach is shown in table 3. We utilize a master scale with 21 notches by assigning numerical values to ratings (Aaa/AAA = 1, Aa1/AA+ = 2, ..., C/D = 21). This approach is common in the relevant literature: Cantor and Packer (1997) and Perry (1985) use 17 rating classes, and Ederington and Yawitz (1987) use 18. Since, in contrast to these studies, our dataset is dominated by low ratings, we break the low segment down further, making a total of 21 classes. Because we want to differentiate the rating classes as widely as possible in the lower segment, we do not use the average historical default rates of the two agencies instead of the numerical rating classes, since in the yearly publications of the rating agencies these default rates are lumped together into one class for all ratings below B3/B-. Therefore, utilizing default rates would have yielded only 17 rating classes.

Besides rating changes, Bloomberg also delivers Watchlist entries. As part of the rating monitoring process, an issuer might be placed on a formal rating review, which is called the Watchlist. These entries signal to the market participants that a rating change in the near future is highly probable, but that the rating analysts need more time to assess the magnitude of the forthcoming rating change. Watchlist announcements are often made after M&A activities or corporate restructuring plans have been published. As one example among several, Hand et al. (1992) provide evidence of significantly abnormal stock returns after announcements of additions to the S&P Watchlist. Furthermore, default rates for issuers placed on the Watchlist of Moody's are different from issuers that do not appear on this list (Keenan et al., 1998).

Hamilton and Cantor (2004) find that the accuracy of default predictions is significantly better after the inclusion of Watchlist information.[§§] Besides, Hamilton and Cantor incorporate Watchlist information into credit ratings by adjusting the rating by two notches upwards in the case of a positive Watchlist entry and two notches downwards in the case of a negative Watchlist entry. Thus, the authors anticipate forthcoming rating events, as in most cases Watchlist additions are followed by rating changes in the same direction. In this study, we make use of Watchlist information by adding 1 to the numerical rating for a negative Watchlist entry and by subtracting 1 from the numerical rating for a positive entry.

# 5 Empirical Results

We first analyze the adjustment of the numerical credit ratings before the default events by using the most recent rating for the following time periods: over 1,440 days, between 1,440 and 1,081 days, between 1,080 and 721 days, between 720 and 541 days, between 540 and 361 days, between 360 and 181 days, between 180 and 91 days and between 90 and 31 days before our defined default event.

Table 4 shows the results for the rating level before default. As a tendency, the closer the default date, the lower the mean ratings of both rating agencies are. On average, Moody's assigns lower ratings than S&P for all eight periods. This result is in line with research into split ratings (Cantor and Packer, 1997, Ederington and Yawitz, 1987, Güttler, forthcoming, and Perry, 1985). Besides the mean rating, the 10%-quantile and the median of ratings assigned by Moody's are always lower than or equal to those assigned by S&P. Another relevant measure is the frequency of investment grade ratings. Enron is a well-known instance of a late downgrade of a borrower to a non-investment grade rating before default. Both Moody's and S&P downgraded this debtor to non-investment grade only a couple of days before it actually de-

[§§] Hamilton and Cantor (2004) also include Outlook information. Since we do not have Outlook information we concentrate on Watchlist additions.

faulted. Since, on the one hand, events like this damage the reputation of credit rating agencies and, on the other hand, are very costly for investors, we believe that the ratio of investment grade rated debtors in a certain time frame prior to the default event is an important quantity with which to measure the timeliness of credit ratings. The frequency of investment grade ratings and the 10%-quantile of ratings by Moody's are equal to or higher than those by S&P for the first four periods, i.e. > 1,440 to 720-541 days before default. This changes in the last four periods before the default event, where Moody's assigns lower ratings according to the 10%-quantile and the frequency of investment grade ratings is also lower.

Table 5 gives the results of our univariate analysis, which is done to detect significant determinants for the credit rating level using nonparametric Wilcoxon rank-sum tests. The anticipation problem hypothesis is supported for the last period, i.e. 90 to 31 days before the default event, for the credit ratings by S&P on the 10% significance level. For the other periods, the coefficient is not significantly different from zero. For Moody's we find no evidence for this hypothesis at all.

Except for the last period of ratings assigned by S&P, in which US issuers are assigned significantly higher ratings, there is no evidence to confirm the home bias hypothesis. Clearer confirmation is found for the incentive problem hypothesis, since for 3 (6) time periods the ratings assigned by Moody's (S&P) for companies with an above-median outstanding debt amount (as our proxy for company size) are significantly better. We also analyze whether telecommunications firms have a lower rating than firms belonging to other sectors. We do indeed observe this pattern for 3 (6) periods for ratings assigned by Moody's (S&P). In addition, we find that fallen angels are assigned better ratings by both agencies in all periods.

To additionally check the characteristics of the defaulted issuers we perform a multivariate analysis of determinants $X_k$ for the credit rating $R$ of debtor $i$ for the 8 different time spans $t$ before default for Moody's and S&P:

$$R_{i,t} = a_t + \sum_{k=1}^{5} l_k X_{k,i,t} + e_{i,t} \qquad (1)$$

where $X_{1,i,t}$ equals 1 if the company $i$ in period $t$ defaulted because of a chapter 11 filing, and zero if not; $X_{2,i,t}$ equals 1 if the company $i$ in period $t$ has its headquarters in the US, and zero if not; $X_{3,i,t}$ is equivalent to the outstanding debt amount at the time of default of the corresponding company $i$ in period $t$ (measured as the natural log of the debt amount in billions of US dollars); $X_{4,i,t}$ equals 1 if company $i$ in period $t$ operates in the telecommunications sector, and zero if not; $X_{5,i,t}$ equals 1 if company $i$ in period $t$ is a fallen angel, zero if not; and $e_{i,t}$ is the random disturbance of issuer $i$ in period $t$. In Eq. (1) $t$ signifies the eight periods before default. Therefore, we conduct eight regressions, i.e. one for each period, for the rating level of Moody's (panel I) and eight additional regressions for S&P (panel II) as a dependent variable.

Table 6 gives the results of the multivariate analysis. As in the preceding univariate analysis we find no evidence to support the anticipation hypothesis. In contrast to the univariate analysis, we find (slight) confirmation of the home bias hypothesis for three periods for Moody's. As in the univariate analysis there is evidence in favor of the incentive problem hypothesis: we find a significant negative correlation between rating and size in six of the eight periods for Moody's and S&P. In other words, bigger firms are assigned better ratings. For the two additional variables we find confirmatory results for the telecommunications sector and the fallen angel coefficient. Obviously, the number of issuers in the regressions varies over the eight periods, and it is not clear whether this variation influences the results. We test this by analyzing a fixed sample with 230 (324) issuers rated by Moody's (S&P) through the whole period from at least 721 days before default without interruption until the default event.[***]

[***] Of course this could also be done with fixed samples from two periods even further away from the default point, but we chose the sixth period in order to be able to work with larger sample sizes.

Table 7 shows the results for this robustness check. These results are almost the same as in table 6. For the telecommunications dummy, the results are less strong for Moody's in two periods only.

Obviously, our analysis lacks additional control variables. Results that are more robust should be obtainable by using additional balance sheet data. For example, significant results for the regression coefficient of the proxy for size could also be due to other factors, e.g., the sounder capital structures of bigger firms. We do not include these variables in our analysis for three reasons:

1) difficulties in comparing balance sheet data produced according to different accounting standards, bearing in mind that we include credit ratings and default data for issuers based in 25 different countries;
2) to avoid a further reduction of the dataset due to missing accounting data;
3) to avoid the exclusion of non-comparable business sectors such as Banking & Financials or Utilities.

Summarizing our results for the determinants of the rating level before default using univariate and multivariate analysis, we find that, except for one period in the univariate analysis, there is no support for the anticipation hypothesis. Even if a default following a chapter 11 filing might be more difficult to anticipate, it seems that the two credit rating agencies are not biased in cases where chapter 11 is the reason for default. For the home bias hypothesis we find only slender evidence in the Moody's results in three periods in the multivariate analysis and in the univariate analysis for the last period of issuers rated by S&P. However, we argue that overall there is no clear support for the home bias hypothesis. In contrast to Beattie and Searle (1992), Nickell et al. (2000), and Shin and Moore (2003) but in concurrence with Ammer and Packer (2000), we find that the US credit rating agencies appear not to favor US issuers. Since we do not have the information sets of the rating agencies, we must obviously be careful in interpreting these quantities. It is also conceivable that the rating agencies have more negative information about US issuers than the credit ratings would indicate, but do not take it fully into account. However, we do find evidence for the incentive problem hypothesis insofar as larger companies have better ratings than smaller ones. Besides, it seems that companies belonging to the telecommunications sector have lower ratings than the rest of the issuers. We find the strongest effect among the fallen angels: formerly investment grade-rated issuers have far better ratings than issuers that have always been rated as non-investment grade throughout our observation period, i.e., from 1990 to 2003.

Next, we apply Granger causality analysis to test the information flow hypothesis, i.e. to test whether one credit rating agency causes the other to adjust its risk assessments, and to test the market anticipation hypothesis.[†††] In contrast to the preceding analysis of the rating level of issuers that subsequently defaulted, we now concentrate on rating changes. Table 8 shows the distribution of the rating changes per issuer for Moody's and S&P. Since the first rating in our dataset serves as an initial rating, we need at least one additional rating change to calculate actual rating changes. Therefore, the size of our dataset declines from 371 in the preceding analysis to 316 issuers with multiple rating changes for Moody's and S&P. For these 316 issuers with multiple rating changes there are 877 rating changes by Moody's and 1,178 rating changes by S&P. Hence, for S&P we find more rating changes per issuer on average. The maximum number of rating changes per issuer is 13 for Moody's and 15 for S&P.

Table 8 also shows the difficulties of our dataset. We have a panel structure with a cross section of 316 issuers and a time series for a section of the issuers. However, the panel is very unbalanced. For 96 issuers we have only one rating change available, i.e. no time series data. Since we analyze multiple rating changes only, our dataset would shrink considerably if we were to use a panel approach. Nevertheless, intuition and the results presented in table 4 give sufficient reason to assume the existence of a strong time trend. Rating downgrades are sharper the closer the default event comes. Therefore, even though we prefer not to use a

[†††] Among others, Ederington and Goh (1998) apply a somewhat similar Granger causality analysis between Moody's rating changes and revisions of stock analysts' forecasts.

panel approach due to data restrictions, we have to control for the time trend by using period dummies for the distance to default.[‡‡‡]

We define two basic sets of Granger causality regression models (Granger, 1969), the first with Moody's as potential rating follower and S&P as potential rating leader (regression model I in panel I of table 9):

$$?R^{M}_{i,t} = a + \sum_{j=1}^{3} ß^{1}_{j}\, ?R^{S}_{i,t-j} + \sum_{j=1}^{3} ß^{2}_{j}\, ?R^{M}_{i,t-j} + e_{i} \qquad (2)$$

where $\Delta R^{M}_{i,t}$ indicates a rating change by Moody's for debtor $i$ at time $t$, and $\Delta R^{S}_{i,t-j}$ specifies the change of the rating for debtor $i$ by S&P for three predefined periods $t-j$:

- $j$ = 1: 1 to 90 days before the rating change of debtor $i$ at time $t$
- $j$ = 2: 91 to 180 days before the rating change of debtor $i$ at time $t$
- $j$ = 3: 181 to 360 days before the rating change of debtor $i$ at time $t$

The variable $\Delta R^{M}_{i,t-j}$ incorporates the lagged rating changes of Moody's for debtor $i$ for the same three periods $t-j$.

The regression with S&P as potential rating follower and Moody's as potential rating leader is defined through the term (regression model I in panel II of table 9):

$$\Delta R^{S}_{i,t} = \alpha + \sum_{j=1}^{3} \beta^{3}_{j} \Delta R^{M}_{i,t-j} + \sum_{j=1}^{3} \beta^{4}_{j} \Delta R^{S}_{i,t-j} + \varepsilon_{i} \qquad (3)$$

To control for the distance to default the rating changes are attributed to 8 periods before the default event by applying 7 dummy variables in regression model II. The last period before default, i.e. in this analysis up to 90 days before default, serves as the reference. Hence we

[‡‡‡] Nevertheless, we have checked with a reduced panel dataset whether fixed effects are observable in the cross section and over the periods. We find significant period fixed effects only. By using period dummies in the pooled OLS analysis, we are able to control for the period effect without losing any data.

define regression model II with Moody's as potential rating follower and S&P as potential rating leader (in panel I of table 9):

$$\Delta R_{i,t}^{M} = \alpha + \sum_{j=1}^{3} \beta_j^{1} \Delta R_{i,t-j}^{S} + \sum_{j=1}^{3} \beta_j^{2} \Delta R_{i,t-j}^{M} + \sum_{w=1}^{7} \gamma_w I_{w,i,t} + \varepsilon_i \tag{4}$$

where $I_{w,i,t}$ are seven indicator variables with the value 1, if the rating change by Moody's took place more than 1,440 days (w = 7), between 1,440 and 1,081 days (w = 6), between 1,080 and 721 days (w = 5), between 720 and 541 days (w = 4), between 540 and 361 days (w = 3), between 360 and 181 days (w = 2), between 180 and 91 days (w = 1) before default and zero otherwise.

The respective regression model II with S&P as potential rating follower and Moody's as potential rating leader is defined through the term (panel II of table 9):

$$\Delta R_{i,t}^{S} = \alpha + \sum_{j=1}^{3} \beta_j^{3} \Delta R_{i,t-j}^{M} + \sum_{j=1}^{3} \beta_j^{4} \Delta R_{i,t-j}^{S} + \sum_{w=1}^{7} \gamma_w I_{w,i,t} + \varepsilon_{i,t} \tag{5}$$

Furthermore, we also include our five known additional variables – reason for default, location of headquarters, debt amount, sector and fallen angel – for regression model III in panel I in table 9, which is defined by

$$\Delta R_{i,t}^{M} = \alpha + \sum_{j=1}^{3} \beta_j^{1} \Delta R_{i,t-j}^{S} + \sum_{j=1}^{3} \beta_j^{2} \Delta R_{i,t-j}^{M} + \sum_{w=1}^{7} \gamma_w I_{w,i,t} + \sum_{k=1}^{5} \lambda_k X_{k,i,t} + \varepsilon_i \tag{6}$$

for Moody's as potential rating follower and S&P as potential rating leader and by

$$\Delta R_{i,t}^{S} = \alpha + \sum_{j=1}^{3} \beta_j^{3} \Delta R_{i,t-j}^{M} + \sum_{j=1}^{3} \beta_j^{4} \Delta R_{i,t-j}^{S} + \sum_{w=1}^{7} \gamma_w I_{w,i,t} + \sum_{k=1}^{5} \lambda_k X_{k,i,t} + \varepsilon_i \tag{7}$$

for S&P as potential rating follower and Moody's as potential rating leader (see panel II in table 9).

For the analysis of the information flow hypothesis we test for the two regression models the null hypotheses $b_j^1 = 0$ and $b_j^3 = 0$. Rejecting the null hypothesis would mean for $b_j^1 \neq 0$ ($b_j^3 \neq 0$) that S&P granger cause Moody's (Moody's granger cause S&P) for the time period $j$ before the rating change in $t$, i.e. that information flows from S&P to Moody's (Moody's to S&P). Unidirectional Granger causality results if we find only $b_j^1 \neq 0$ or $b_j^3 \neq 0$ on common significance levels. Two-way causality results for significant results for both $b_j^1 \neq 0$ and $b_j^3 \neq 0$.

For the coefficients of the lagged rating changes of the potential rating follower we test the null hypotheses $b_j^2 = 0$ and $b_j^4 = 0$. For the period dummies in the regression models II and III we test the null hypotheses $?_1 = 0, \ldots, ?_7 = 0$. For the five additional coefficients in regression model III we test the null hypotheses $?_1 = 0, \ldots, ?_5 = 0$.

Results for the Granger analysis are given in table 9. We find clear evidence for the information flow hypothesis, i.e. that rating changes by one credit rating agency increase the probability of a rating change by the other credit rating agency in the same direction, since we observe two-way Granger causality. Since $b_1^1 > 0$ and $b_2^1 > 0$ on the 1% significance level in all three regression models, S&P granger cause Moody's in the time periods 1-90 and 91-181 days before default. Because we also observe $b_1^3 > 0$ on the 1% significance level and $b_2^3 > 0$ on the 1% significance level in the first two regression models and $b_2^3 > 0$ on the 5% significance level in the third regression model, this holds for Moody's as the rating follower, too. These results are stable even after adding the period dummies in regression models II and III. We find no evidence to suggest that Moody's has a leading position because of its more conservative ratings, as one might have expected.

Adding the period dummies into the regression models (II and III) increases the adjusted $R^2$ sharply. For Moody's as rating follower it jumps from 16.74 to 25.56% and for S&P as rating follower it more than doubles from 12.55 to 27.54%. Except for the period 91 – 180 days before default for Moody's, the respective coefficient is always significantly less than zero on the 1% significance level. Since the period less than 91 days before default serves as our reference, rating changes – which are mostly downgrades – in the periods further away from the default event are less severe. Given the high explanatory power of the period dummies, the results of regression model I do not seem to be robust.

We find greater differences for the lagged coefficients of the respective rating follower's own rating changes. For Moody's as rating follower, $ß_1^2 < 0$ in all three regression models. This effect is stronger in regression model II (and III) after adding the period dummies. Rating changes of Moody's in the other two periods, 91 – 180 and 181 – 360, do not seem to influence the magnitude of the analyzed rating changes. Whereas for S&P as a rating follower in regression model I $ß_j^4 = 0$, the influence of S&P's own rating changes alter sharply after adding the period dummies in regression models II and III: then $ß_1^4 < 0$ on the 1% significance level and $ß_2^4 < 0$ on the 5% significance level. How can these results for the agencies' own lagged rating changes be interpreted? Since the coefficients for the last period (last two periods) is negative for Moody's (S&P), the rating changes – which are mainly downgrades in our sample – are less severe when the agency has changed its own rating in the last period (last two periods) for Moody's (S&P).[§§§] These results signify that the two rating agencies might apply a policy of taking a severe downgrade through several mild downgrades. The rationale for this policy might be to avoid a pronounced deterioration of the agency's relationship with

[§§§] Our results add further evidence to that of the existing studies of serial correlation of rating changes: Altman and Kao (1992) detect positive serial autocorrelation in ratings of S&P when the initial rating change was a downgrade; Lando and Skødeberg (2002) find positive serial correlations for downgrades in a sample of debtors rated by S&P; Christensen et al. (2004) provide this kind of evidence also for a sample of issuers rated by Moody's.

the rated company. This effect is somewhat stronger for S&P, which might be mainly due to the higher numbers of rating changes by this agency.

Regarding the other explanatory variables for rating changes, our analysis supports the home bias hypothesis for Moody's on the 10% significance level and for S&P on the 1% significance level. Issuers with headquarters in the US are less sharply downgraded than non-US issuers. For S&P this result strengthens the results of the univariate and multivariate analysis for the last period before default (see tables 5 and 6). For rating changes by Moody's we also find support for the incentive problem hypothesis on the 5% significance level. Hence, larger issuers seem to be downgraded less severely than smaller issuers. Unexpected results are found for changes in the rating of issuers which defaulted because of a chapter 11 filing. In these cases, the downgrades by Moody's are more pronounced than those of the other issuers. We find no significant results regarding the sector or the rating status (fallen angel) for either of the rating agencies.

## 6 Summary

Using a dataset consisting of 371 issuers that defaulted in the time period 1999 to 2003, with 1,345 long-term, unsecured issuer ratings assigned by Moody's and 1,789 by S&P, this study has provided additional insights into determinants of the rating level of these issuers and into the leader-follower relationship between Moody's and S&P. The evidence for the rating level suggests that Moody's assigns lower ratings than S&P for all observed periods before the default event, which is in line with research into split ratings. Besides, larger issuers and fallen angels have higher ratings and issuers belonging to the telecommunications sector have lower ratings. Furthermore, we observe two-way Granger causality, which signifies information flow between the two rating agencies. Since lagged rating changes influence the magnitude of an agency's own rating changes, it would appear that the two rating agencies apply a policy of taking a severe downgrade through several mild downgrades. Further, our analysis of rating changes supports the home bias hypothesis for Moody's and S&P. Hence, issuers with head-quarters in the US are less sharply downgraded than non-US issuers. For rating changes by Moody's we also find support for the incentive problem hypothesis, i.e. larger issuers seem to be downgraded less severely than smaller issuers.

## Table 1: Characteristics of 371 defaulted firms with multiple ratings by Moody's and S&P

371 defaults occurred in the years 1999 to 2003 involving issuers rated by Moody's and S&P at the time of default. The reasons for default are based on information reported by Moody's. We define the date of the default event as the earliest date reported by either of the two agencies. As the reported debt amount, we use the reported values in millions of US dollars. If Moody's and S&P do not report an identical default date and/or if there are discrepancies in the reported debt amount, we calculate the mean outstanding debt amount between Moody's and S&P if they report the same default date, or, if they do not report the same date, we use the debt amount as of the earlier default date. An issuer is defined as a "fallen angel" if it had an investment grade rating at some time during the observation period 1990 to 2003 but was subsequently downgraded to non-investment grade before the end of 2003. According to table 3 this means a downgrade to a rating worse than 10.

| | Number of observations | Frequency |
|---|---|---|
| **I. Reason for default** | | |
| Missed interest payment | 203 | 0.5472 |
| Chapter 11 | 90 | 0.2426 |
| Distressed exchange | 30 | 0.0809 |
| Bankruptcy | 12 | 0.0323 |
| Grace period default | 10 | 0.0270 |
| Suspension of payments | 9 | 0.0243 |
| Missed principal and interest payments | 8 | 0.0216 |
| Missed principal payment | 6 | 0.0162 |
| Others | 3 | 0.0081 |
| **II. Headquarters** | | |
| USA | 291 | 0.7844 |
| UK | 16 | 0.0431 |
| Canada | 16 | 0.0431 |
| Argentina | 11 | 0.0296 |
| Mexico | 9 | 0.0243 |
| Greece | 4 | 0.0108 |
| Netherlands | 3 | 0.0081 |
| Others | 21 | 0.0566 |
| **III. Debt amount (USD million)** | | |
| 0-100 | 69 | 0.1860 |
| 100-250 | 137 | 0.3693 |
| 250-500 | 63 | 0.1698 |
| 500-1,000 | 53 | 0.1429 |
| 1,000-2,500 | 31 | 0.0836 |
| 2,500-5,000 | 12 | 0.0323 |
| 5,000-10,000 | 5 | 0.0135 |
| >10,000 | 1 | 0.0027 |
| **IV. Sector** | | |
| Telecommunications | 62 | 0.1671 |
| Transportation & Shipping | 26 | 0.0701 |
| Miscellaneous | 23 | 0.0620 |
| Metals & Mining | 22 | 0.0593 |
| Construction, Building, & Real Estate | 19 | 0.0512 |
| Industrial | 17 | 0.0458 |
| Printing, Publishing, & Broadcasting | 17 | 0.0458 |
| Retail | 15 | 0.0404 |
| Chemicals, Plastics, & Rubber | 14 | 0.0377 |
| Electronics | 14 | 0.0377 |
| Beverage, Food, & Tobacco | 13 | 0.0350 |
| Consumer Products | 13 | 0.0350 |
| Healthcare, Education, & Childcare | 12 | 0.0323 |
| Automobile | 11 | 0.0296 |
| Banking & Financial | 11 | 0.0296 |
| Hotels, Casinos, & Gaming | 11 | 0.0296 |
| Technology | 11 | 0.0296 |
| Oil & Gas | 10 | 0.0270 |
| Others | 48 | 0.1294 |
| **V. Rating history** | | |
| Non-Investment grade | 341 | 0.9191 |
| Fallen angel | 30 | 0.0809 |

## Table 2: Distribution of defaults and the amount of outstanding debt over time

This table shows the distribution of 371 defaults which occurred in the years 1999 to 2003 involving issuers rated by Moody's and S&P. We define the date of the default event as the earliest date reported by either of the two agencies. As the reported debt amount, we use the reported values in millions of US dollars. If Moody's and S&P do not report an identical default date and/or if there are discrepancies in the reported debt amount we calculate the mean outstanding debt amount between Moody's and S&P if they report the same default date, or, if they do not report the same date, we use the debt amount as of the earlier default date.

| | **1999** | **2000** | **2001** | **2002** | **2003** |
|---|---|---|---|---|---|
| Number of defaults | 34 | 83 | 117 | 91 | 46 |
| Median outstanding debt | 159.75 | 158.50 | 225.00 | 300.00 | 277.50 |
| Mean outstanding debt | 280.24 | 314.51 | 687.29 | 1054.66 | 479.19 |

## Table 3: Mapping of the rating systems of Moody's and S&P

This table shows the mapping of the rating classes of Moody's and S&P to a numerical rating scale. Numerical ratings of 10 and better signify investment grade. We incorporate positive (negative) Watchlist additions by increasing (decreasing) the rating by 1 notch, e.g. an issuer with a rating of BBB with a positive Watchlist entry gets a mapped rating of 8 instead of the numerical rating of 9 that it would have received without the positive Watchlist entry.

| Moody's | S&P | Numerical rating |
|---|---|---|
| Aaa | AAA | 1 |
| Aa1 | AA+ | 2 |
| Aa2 | AA | 3 |
| Aa3 | AA- | 4 |
| A1 | A+ | 5 |
| A2 | A | 6 |
| A3 | A- | 7 |
| Baa1 | BBB+ | 8 |
| Baa2 | BBB | 9 |
| Baa3 | BBB- | 10 |
| Ba1 | BB+ | 11 |
| Ba2 | BB | 12 |
| Ba3 | BB- | 13 |
| B1 | B+ | 14 |
| B2 | B | 15 |
| B3 | B- | 16 |
| Caa1 | CCC+ | 17 |
| Caa2 | CCC | 18 |
| Caa3 | CCC- | 19 |
| Ca | CC | 20 |
| C | D | 21 |

## Table 4: Rating adjustments before default

For the analysis of rating adjustments before default, we arrange the rating history of all defaulted issuers according to eight time periods before the defined default date, e.g. the rightmost column "90-31" gives the quantities for the period 90 to 31 days before default. We use the mapped, numerical ratings of table 3 from 1 (Aaa/AAA) to 21 (C/D) with adjustments for Watchlist additions. The frequency of investment grade rated issuers corresponds to the number of issuers with a rating of 10 and better in the respective time period divided by the total number of observations in the respective time period.

| | Ratings, days to default | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | >1,440 | 1,440-1,081 | 1,080-721 | 720-541 | 540-361 | 360-181 | 180-91 | 90-31 |
| **Panel I: Moody's** | | | | | | | | |
| Mean | 13.4891 | 13.9348 | 14.7913 | 15.0696 | 15.4204 | 16.1758 | 16.9528 | 17.6530 |
| 10%-quantile | 18 | 17 | 18 | 18 | 18 | 19 | 20 | 20 |
| Median | 14 | 15 | 15 | 15 | 16 | 16 | 17 | 18 |
| 90%-quantile | 9 | 9 | 11 | 11.2 | 13 | 14 | 15 | 15 |
| Observations | 92 | 138 | 230 | 273 | 314 | 347 | 360 | 366 |
| Frequency of investment grade | 0.2609 | 0.1812 | 0.0957 | 0.0842 | 0.0701 | 0.0461 | 0.0306 | 0.0164 |
| **Panel II: S&P** | | | | | | | | |
| Mean | 13.1084 | 13.2984 | 13.7006 | 13.9655 | 14.2964 | 15.0652 | 15.9838 | 16.9946 |
| 10%-quantile | 15 | 16 | 16 | 16 | 16 | 17 | 19 | 20 |
| Median | 14 | 14 | 14 | 14 | 14 | 15 | 16 | 17 |
| 90%-quantile | 9 | 10 | 11 | 12 | 12 | 13 | 13 | 14 |
| Observations | 166 | 248 | 324 | 348 | 361 | 368 | 371 | 371 |
| Frequency of investment grade | 0.1566 | 0.1169 | 0.0864 | 0.0690 | 0.0609 | 0.0516 | 0.0404 | 0.0216 |

## Table 5: Univariate comparative statics of determinants of the rating level

For the analysis of five determinants of the rating level we use the mapped, numerical ratings of table 3 from 1 (Aaa/AAA) to 21 (C/D) with adjustment for Watchlist additions. An issuer is defined as a "fallen angel" if it had an investment grade rating at some time during the observation period 1990 to 2003 but was subsequently downgraded to non-investment grade before the end of 2003. The table shows results of Wilcoxon rank-sum tests for two subsamples, and for all determinants. Results are given for all eight time periods before the defined default date, e.g. the rightmost column "90-31" gives the quantities for the period 90 to 31 days before default. Two-sided significance levels are given as ***, **, and * representing 1%, 5%, and 10% respectively.

| | | Average rating, days to default | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | >1,440 | 1,440-1,081 | 1,080-721 | 720-541 | 540-361 | 360-181 | 180-91 | 90-31 |
| **Panel I: Moody's** | | | | | | | | | |
| Default reason | Chapter 11 | 13.2222 | 13.6053 | 14.6964 | 14.9851 | 15.3514 | 15.9136 | 16.7108 | 17.5476 |
| | Non-Chapter 11 | 13.6000 | 14.0600 | 14.8218 | 15.1534 | 15.5578 | 16.3133 | 17.0530 | 17.6844 |
| | Difference | -0.3778 | -0.4547 | -0.1254 | -0.1683 | -0.2064 | -0.3997 | -0.3422 | -0.1368 |
| Headquarters | US | 13.5753 | 14.0288 | 14.9006 | 15.1787 | 15.5228 | 16.2390 | 16.9502 | 17.5749 |
| | Non-US | 13.1579 | 13.6471 | 14.4746 | 14.6522 | 15.1250 | 16.1429 | 17.0152 | 17.9726 |
| | Difference | 0.4174 | 0.3818 | 0.4260 | 0.5266 | 0.3978 | 0.0961 | -0.0650 | -0.3977 |
| Debt amount | Larger than median | 12.1957 | 13.1739 | 14.0435 | 14.3015 | 14.7452 | 15.7110 | 16.7000 | 17.6612 |
| | Lower than median | 14.7826 | 14.6957 | 15.5391 | 15.7766 | 16.1034 | 16.7376 | 17.2155 | 17.6448 |
| | Difference | -2.5870*** | -1.5217** | -1.4957*** | -1.4751*** | -1.3582*** | -1.0266* | -0.5155 | 0.0164 |
| Sector | Telecommunications | 15.3333 | 15.1111 | 15.0500 | 15.3137 | 15.5172 | 16.3607 | 17.1967 | 18.3387 |
| | Non-telecommunications | 13.2125 | 13.7583 | 14.7368 | 14.9721 | 15.4186 | 16.1502 | 16.8636 | 17.4933 |
| | Difference | 2.1208** | 1.3528** | 0.3132 | 0.3417 | 0.0986 | 0.2105 | 0.3331 | 0.8454*** |
| Rating | Fallen angel | 10.1538 | 10.1429 | 10.8966 | 10.9310 | 11.2069 | 12.2000 | 14.1000 | 16.0333 |
| | Non-investment grade | 14.8030 | 14.9000 | 15.3532 | 15.5615 | 15.8491 | 16.5521 | 17.2121 | 17.7976 |
| | Difference | -4.6492*** | -4.7571*** | -4.4567*** | -4.6304*** | -4.6422*** | -4.3521*** | -3.1121*** | -1.7643*** |
| Observations | | 92 | 138 | 230 | 273 | 314 | 347 | 360 | 366 |

| | | Average rating, days to default | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | >1,440 | 1,440-1,081 | 1,080-721 | 720-541 | 540-361 | 360-181 | 180-91 | 90-31 |
| **Panel II: S&P** | | | | | | | | | |
| Default reason | Chapter 11 | 12.7556 | 13.0678 | 13.5676 | 13.8701 | 14.1852 | 14.9759 | 15.6071 | 16.5595 |
| | Non-Chapter 11 | 13.2397 | 13.2517 | 13.7400 | 13.9926 | 14.3286 | 15.0912 | 16.0941 | 17.1220 |
| | Difference | -0.4841 | -0.1840 | -0.1724 | -0.1225 | -0.1434 | -0.1153 | -0.4869 | -0.5624* |
| Headquarters | US | 13.2132 | 13.3781 | 13.7500 | 14.0108 | 14.3028 | 15.0517 | 15.9038 | 16.8316 |
| | Non-US | 12.6333 | 13.6757 | 13.6429 | 14.1064 | 14.3750 | 15.1268 | 16.2338 | 17.5875 |
| | Difference | 0.5799 | -0.2976 | 0.1071 | -0.0956 | -0.0722 | -0.0750 | -0.3300 | -0.7559*** |
| Debt amount | Larger than median | 12.3780 | 12.7903 | 13.1728 | 13.4310 | 13.7624 | 14.6033 | 15.7568 | 17.1135 |
| | Lower than median | 13.8214 | 13.7179 | 14.2284 | 14.5000 | 14.8333 | 15.5272 | 16.2097 | 16.8763 |
| | Difference | -1.4434*** | -0.9276** | -1.0556*** | -1.0690*** | -1.0709*** | -0.9239*** | -0.4529 | 0.2372 |
| Sector | Telecommunications | 14.2727 | 13.2703 | 14.2245 | 14.4561 | 14.7000 | 15.3387 | 16.5161 | 17.9677 |
| | Non-telecommunications | 12.9306 | 13.3515 | 13.5425 | 13.8689 | 14.2292 | 14.9900 | 15.8770 | 16.7994 |
| | Difference | 1.3422*** | -0.0812 | 0.6820*** | 0.5872*** | 0.4708** | 0.3487 | 0.6391** | 1.1684*** |
| Rating | Fallen angel | 9.5200 | 9.3704 | 10.0000 | 10.4286 | 10.7500 | 11.5517 | 13.1333 | 15.7333 |
| | Non-investment grade | 13.7447 | 13.7783 | 14.0507 | 14.2750 | 14.5946 | 15.3658 | 16.2346 | 17.1056 |
| | Difference | -4.2247*** | -4.4079*** | -4.0507*** | -3.8464*** | -3.8446*** | -3.8141*** | -3.1013*** | -1.3722*** |
| Observations | | 166 | 248 | 324 | 348 | 361 | 368 | 371 | 371 |

## Table 6: Regression results of determinants of the rating level

The table reports the results of eight regressions for each rating agency. Panel I (II) shows results for the rating level of Moody's (S&P) as dependent variable. The dependent variables are the rating levels $R_i$ for the eight periods before the default event. As ratings we use the mapped, numerical ratings of table 3 from 1 (Aaa/AAA) to 21 (C/D) with adjustment for Watchlist additions. Independent variables are a dummy that takes the value 1 if the company defaults because of chapter 11, a second dummy that takes the value 1 if the company has its headquarters in the US, the size of the issuer (substituted by the natural log of the debt amount at the time of default), a third dummy that takes the value 1 if the company is mainly engaged in the telecommunications sector, and a fourth dummy that takes the value 1 if the company is classified as a fallen angel. An issuer is defined as a "fallen angel" if it had an investment grade rating at some time during the observation period 1990 to 2003 but was subsequently downgraded to non-investment grade before the end of 2003. We apply Heteroskedasticity-consistent standard errors (White 1980). Two-sided significance levels are given as ***, **, and * representing 1%, 5%, and 10% respectively.

| | Rating, days to default | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | >1,440 | 1,440-1,081 | 1,080-721 | 740-541 | 540-361 | 360-181 | 180-91 | 90-31 |
| **Panel I: Moody's** | | | | | | | | |
| Intercept | 16.0986*** | 16.0135*** | 17.0781*** | 17.5107*** | 17.6504*** | 17.8713*** | 18.4136*** | 18.8263*** |
| Chapter 11 | -0.0859 | -0.1125 | 0.1750 | 0.1508 | 0.1468 | -0.1321 | -0.1093 | 0.1087 |
| US | 0.6190 | 0.7379 | 0.6110* | 0.5832** | 0.4603* | 0.3398 | 0.0525 | -0.2235 |
| Size | -0.3844* | -0.3534* | -0.4409*** | -0.4789*** | -0.4244*** | -0.3072** | -0.2418 | -0.1924 |
| Telecommunications | 2.9247*** | 2.1168*** | 1.0968*** | 1.0312*** | 0.7015** | 0.6246* | 0.5602 | 0.9924*** |
| Fallen angel | -4.0844*** | -4.1996*** | -3.7808*** | -3.8767*** | -3.9757*** | -3.8448*** | -2.7355*** | -1.5078** |
| Observations | 92 | 138 | 230 | 273 | 314 | 347 | 360 | 366 |
| Adjusted $R^2$ | 0.4384 | 0.4324 | 0.3573 | 0.3661 | 0.3318 | 0.2486 | 0.1241 | 0.0589 |
| **Panel II: S&P** | | | | | | | | |
| Intercept | 14.4540*** | 14.9872*** | 15.6811*** | 15.7647*** | 16.3614*** | 17.2581*** | 17.9678*** | 18.3902*** |
| Chapter 11 | -0.2072 | -0.0068 | 0.0896 | 0.1314 | 0.1225 | 0.1442 | -0.1753 | -0.2595 |
| US | 0.4417 | 0.4453 | 0.3366 | 0.2682 | 0.0770 | -0.0551 | -0.2099 | -0.4434 |
| Size | -0.2262 | -0.3345** | -0.3886*** | -0.3538*** | -0.3721*** | -0.3703*** | -0.3100** | -0.2003 |
| Telecommunications | 1.7387*** | 1.7557*** | 1.2869*** | 1.1276*** | 0.9706*** | 0.7580** | 0.9163** | 1.2521*** |
| Fallen angel | -3.854*** | -3.8655*** | -3.4681*** | -3.3036*** | -3.2901*** | -3.2868*** | -2.6378*** | -1.0838 |
| Observations | 166 | 248 | 324 | 348 | 361 | 368 | 371 | 371 |
| Adjusted $R^2$ | 0.4035 | 0.4327 | 0.3426 | 0.3083 | 0.2789 | 0.2341 | 0.1354 | 0.0559 |

## Table 7: Regression results of determinants of the rating level for a fixed sample

The table reports the results of six regressions for each rating agency for a fixed sample for each rating agency. We use the 230 (324) issuers of the sixth period before default for all regressions to avoid the influence of the changing sample composition. Panel I (II) shows results for the rating level of Moody's (S&P) as dependent variable. The dependent variables are the rating levels $R_i$ for the six periods before the default event. As ratings we use the mapped, numerical ratings of table 3 from 1 (Aaa/AAA) to 21 (C/D) with adjustment for Watchlist additions. Independent variables are a dummy that takes the value 1 if the company defaults because of chapter 11, a second dummy that takes the value 1 if the company has its headquarters in the US, the size of the issuer (substituted by the natural log of the debt amount at the time of default), a third dummy that takes the value 1 if the company is mainly engaged in the telecommunications sector, and a fourth dummy that takes the value 1 if the company is classified as an fallen angel. An issuer is defined as a "fallen angel" if it had an investment grade rating at some time during the observation period 1990 to 2003 but was subsequently downgraded to non-investment grade before the end of 2003. We apply Heteroskedasticity-consistent standard errors (White 1980). Two-sided significance levels are given as ***, **, and * representing 1%, 5%, and 10% respectively.

| | **Rating, days to default** | | | | | |
|---|---|---|---|---|---|---|
| | 1,080-721 | 740-541 | 540-361 | 360-181 | 180-91 | 90-31 |
| **Panel I: Moody's** | | | | | | |
| Intercept | 17.0781*** | 17.1867*** | 17.3945*** | 17.8659*** | 18.6063*** | 19.1281*** |
| Chapter 11 | 0.1750 | 0.2771 | 0.3339 | 0.0011 | 0.0242 | 0.3829 |
| US | 0.6110* | 0.5768* | 0.5586* | 0.5640 | 0.1740 | -0.1184 |
| Size | -0.4409*** | -0.4200** | -0.3970** | -0.3226* | -0.2757 | -0.2523 |
| Telecommunications | 1.0968*** | 0.8301** | 0.6303 | 0.7114 | 0.6952 | 1.2071** |
| Fallen angel | -3.7808*** | -3.966*** | -4.0309*** | -4.0615*** | -2.8990*** | -1.7326*** |
| Observations | 230 | 230 | 230 | 230 | 230 | 230 |
| Adjusted $R^2$ | 0.3573 | 0.3634 | 0.3498 | 0.2901 | 0.1538 | 0.0864 |
| **Panel II: S&P** | | | | | | |
| Intercept | 15.6811*** | 15.7972*** | 16.3822*** | 17.2863*** | 18.0674*** | 18.4932*** |
| Chapter 11 | 0.0896 | 0.1181 | 0.0742 | 0.0586 | -0.1762 | -0.1935 |
| US | 0.3366 | 0.3170 | 0.1395 | 0.0314 | -0.3567 | -0.4849 |
| Size | -0.3886*** | -0.3693*** | -0.3832*** | -0.3822*** | -0.2994* | -0.2205 |
| Telecommunications | 1.2869*** | 1.0473*** | 0.8415*** | 0.7218* | 0.7944* | 1.2437** |
| Fallen angel | -3.4681*** | -3.2426*** | -3.2379*** | -3.1926*** | -2.5801*** | -0.7922 |
| Observations | 324 | 324 | 324 | 324 | 324 | 324 |
| Adjusted $R^2$ | 0.3426 | 0.3090 | 0.2809 | 0.2294 | 0.1234 | 0.0434 |

## Table 8: Distribution of the number of rating changes per issuer

This table shows the distribution of the number of rating changes per issuer. For 316 issuers with multiple rating changes there are 877 rating changes by Moody's and 1,178 rating changes by S&P.

| | **Number of observations** | | **Frequency** | |
|---|---|---|---|---|
| | Moody's | S&P | Moody's | S&P |
| 1 | 96 | 41 | 30.38% | 12.97% |
| 2 | 89 | 73 | 28.16% | 23.10% |
| 3 | 51 | 67 | 16.14% | 21.20% |
| 4 | 26 | 43 | 8.23% | 13.61% |
| 5 | 24 | 41 | 7.59% | 12.97% |
| 6 | 12 | 19 | 3.80% | 6.01% |
| 7 | 5 | 9 | 1.58% | 2.85% |
| 8 | 8 | 6 | 2.53% | 1.90% |
| 9 | 1 | 4 | 0.32% | 1.27% |
| > 9 | 4 | 13 | 1.27% | 4.11% |
| all | 316 | 316 | 100.00% | 100.00% |

## Table 9: Regression results of the Granger analysis

This table shows results of the Granger analysis applying OLS. The dependent variables are rating changes $?R_{i,t}$ by Moody's in panel I and rating changes by S&P in panel II. We use the mapped, numerical ratings of table 3 from 1 (Aaa/AAA) to 21 (C/D) with adjustment for Watchlist additions. For 316 issuers we analyze 877 rating changes by Moody's (panel I) and 1,178 rating changes by S&P (panel II). The independent variables of regression model I are lagged rating changes by Moody's and S&P for three time periods (1-90, 91-180, and 181-360 days) before the respective rating change. In regression models II and III the rating changes are attributed to eight periods before the default event to control for the distance to default by applying seven dummy variables. The last period before default, i.e. in this analysis up to 90 days before default, serves as the reference. Further independent variables of regression model III are a dummy that takes the value 1 if the company defaults because of chapter 11, a second dummy that takes the value 1 if the company has its headquarters in the US, the size of the issuer (substituted by the natural log of the debt amount at the time of default), a third dummy that takes the value 1 if the company is mainly engaged in the telecommunications sector, and a fourth dummy that takes the value 1 if the company is classified as a fallen angel. An issuer is defined as a "fallen angel" if it had an investment grade rating at some time during the observation period 1990 to 2003 but was subsequently downgraded to non-investment grade before the end of 2003. We apply Heteroskedasticity-consistent standard errors (White 1980). Two-sided significance levels are given as ***, **, and * representing 1%, 5%, and 10% respectively.

| | **Regression I** | | **Regression II** | | **Regression III** | |
|---|---|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error | Coefficient | Standard Error |
| **Panel I: Moody's rating change as dependent variable** | | | | | | |
| Intercept | 0.9462*** | 0.0622 | 1.5946*** | 0.1189 | 1.9541*** | 0.2013 |
| ? Rating by Moody's 1-90 days before | -0.0971* | 0.0584 | -0.1756*** | 0.0598 | -0.1232** | 0.0626 |
| ? Rating by Moody's 91-180 days before | 0.0999 | 0.0740 | 0.0167 | 0.0690 | 0.0534 | 0.0689 |
| ? Rating by Moody's 181-360 days before | -0.0487 | 0.0715 | -0.0258 | 0.0697 | -0.0352 | 0.0692 |
| ? Rating by S&P 1-90 days before | 0.4107*** | 0.0387 | 0.3076*** | 0.0416 | 0.2841*** | 0.0409 |
| ? Rating by S&P 91-180 days before | 0.2760*** | 0.0683 | 0.1719*** | 0.0625 | 0.1433** | 0.0605 |
| ? Rating by S&P 181-360 days before | 0.0923 | 0.0642 | 0.0332 | 0.0582 | 0.0056 | 0.0570 |
| 91 - 180 days to default | | | -0.0591 | 0.1286 | -0.0951 | 0.1295 |
| 181 - 360 days to default | | | -0.3230*** | 0.1243 | -0.3702*** | 0.1251 |
| 361 - 540 days to default | | | -0.7264*** | 0.1710 | -0.8084*** | 0.1718 |
| 541 - 720 days to default | | | -0.9585*** | 0.1961 | -1.0292*** | 0.1905 |
| 721 - 1,080 days to default | | | -0.8978*** | 0.1857 | -0.9538*** | 0.1853 |
| 1,081 - 1,440 days to default | | | -1.6015*** | 0.2964 | -1.6478*** | 0.2974 |
| > 1,440 days to default | | | -1.2264*** | 0.1939 | -1.2947*** | 0.1901 |
| Chapter 11 | | | | | 0.2574** | 0.1102 |
| US | | | | | -0.2331* | 0.1302 |
| Size | | | | | -0.0713** | 0.0305 |
| Telecommunications | | | | | -0.0247 | 0.1003 |
| Fallen angel | | | | | -0.1032 | 0.1339 |
| Observations | 877 | | 877 | | 877 | |
| Adjusted $R^2$ | 0.1674 | | 0.2556 | | 0.2711 | |

| | Regression I | | Regression II | | Regression III | |
|---|---|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error | Coefficient | Standard Error |
| **Panel II: S&P rating change as dependent variable** | | | | | | |
| Intercept | 0.9507*** | 0.0575 | 2.2019*** | 0.1211 | 2.2356*** | 0.1891 |
| ? Rating by S&P 1-90 days before | -0.0112 | 0.0678 | -0.1963*** | 0.0656 | -0.1912*** | 0.0671 |
| ? Rating by S&P 91-180 days before | -0.0126 | 0.0842 | -0.1731** | 0.0751 | -0.1846** | 0.0754 |
| ? Rating by S&P 181-360 days before | 0.1072 | 0.0751 | 0.0178 | 0.0624 | -0.0122 | 0.0642 |
| ? Rating by Moody's 1-90 days before | 0.4451*** | 0.0581 | 0.2759*** | 0.0558 | 0.2870*** | 0.0557 |
| ? Rating by Moody's 91-180 days before | 0.3079*** | 0.0620 | 0.1626*** | 0.0602 | 0.1782*** | 0.0600 |
| ? Rating by Moody's 181-360 days before | 0.0974 | 0.0829 | 0.0781 | 0.0707 | 0.0744 | 0.0707 |
| 91 - 180 days to default | | | -0.6290*** | 0.1346 | -0.6405*** | 0.1358 |
| 181 - 360 days to default | | | -1.0732*** | 0.1360 | -1.0848*** | 0.1370 |
| 361 - 540 days to default | | | -1.2246*** | 0.1547 | -1.2447*** | 0.1554 |
| 541 - 720 days to default | | | -1.4182*** | 0.1597 | -1.4286*** | 0.1593 |
| 721 - 1080 days to default | | | -1.5621*** | 0.1580 | -1.5536*** | 0.1564 |
| 1081 - 1440 days to default | | | -2.1508*** | 0.2229 | -2.1423*** | 0.2230 |
| > 1440 days to default | | | -2.2005*** | 0.1923 | -2.2105*** | 0.1913 |
| Chapter 11 | | | | | 0.0147 | 0.0994 |
| US | | | | | -0.3275*** | 0.1236 |
| Size | | | | | 0.0117 | 0.0276 |
| Telecommunications | | | | | -0.0883 | 0.1003 |
| Fallen angel | | | | | -0.1624 | 0.1264 |
| Observations | 1,178 | | 1,178 | | 1,178 | |
| Adjusted $R^2$ | 0.1255 | | 0.2754 | | 0.2793 | |

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