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Are Credit Ratings Valuable Information?

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Non-technical Summary

Credit ratings are frequently used as information for potential lenders concerning the risk of a debt. The importance of ratings will most likely even increase, given that the New Basle Capital Accord (Basle II agreement) asks for more careful credit management of banks. Banks are advised to use ratings from external sources or to develop an internal system of risk evaluation in order to avoid unexpected loan defaults of their borrowers .

We present an empirical test on the predictive performance of ratings by the most important credit rating agency Creditreform in Germany. In particular we estimate whether the ratings can predict the default risk of German firms. Publicly available information like industry classification, firms size, labor productivity and other variables are used in the first place. Secondly the ratings are included in the regressions and the additional value of this information is systematically compared.

We employ two cross-sectional samples on Western German manufacturing firms consisting of 71,479 observations in 1999 and 79,290 in 2000 - with defaults in the following period only 1,828 and 2,101 cases, respectively. We estimate Probit models on future defaults (in period t+1) and use the credit rating from period t among the other variables as explanatory variables.

The rating of Creditreform is in fact drastically improving the predictive power concerning default risks. However some puzzles remain. On one hand, the publicly available information has still some additional explanatory power and, on the other hand, firm size has a positive impact on a default once a rating is included. Thus we conclude that, first, the rating is not informationally efficient and, second, Creditreform overemphasizes firm size in the construction of the rating index.

On the basis of a simple theoretical model, we compare an investment into a safe loan with a risky credit for which a positive default probability exists. In particular, for different ratings the expected default probabilities are calculated and based on these the critical interest rates are determined which are necessary to cover the expected losses and yield in addition the return from a safe investment. In the cases of the two worst rating categories the default probability is so high that no reasonable interest rate can compensate for the risk of loss of the whole credit. However, even a rating in the third worst category (4 out of the range 1-6) is associated with an interest rate of 9.5% in comparison to a save return of 3% if both investments are required to yield the same expected return. Hence if in line with the New

Basle Capital accord risk is accurately taken into account, the interest spread will be much more pronounced than it is currently the case.

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Abstract

Credit ratings are commonly used by lenders to assess the default risk, because every credit is connected with a possible loss. If the probability of a default is above a certain threshold, a credit will not be provided. The purpose of this paper is to test whether credit ratings contribute valuable information on the creditworthiness of firms. Employing a large sample of Western German manufacturing firms, we investigate loan defaults. First, we estimate Probit models with publicly available information. Subsequently, we additionally use a credit rating and show that it contributes significantly to the regression fit. However, the publicly available information has an independent effect aside of the ratings. Simple calculations demonstrate that the interest rate has to increase significantly to compensate for a possible loss in case of default, if a firm has a weak rating.

Keywords: Credit Rating, Insolvency, Loan Default, Discrete Regression Models
JEL-Classification: C25, G33

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1 Introduction

It is a trivial statement that giving a credit to a firm is necessarily a risky undertaking. The firm may have financial problems and in the worst case may become bancrupt. In order to reduce this risk, a lender will try to get some information about the financial status of the firm in question.

Credit rating agencies offer their services to potential lenders concerning the probability of default of a firm in question. Usually this is done by a classification ranging from statement like "excellent" to "very bad" and based on this classification the lender can judge how large the risk can be expected. This service is used by many institutions like banks, insurance companies or suppliers. Recently the importance of these ratings has even increased as the so-called "Basle II Capital Accord" requires that banks use external or internal ratings for determining the interest rate for individual credits to a specific firm (see e.g. Secretariat of the Basle Committee on Banking Supervision, 2003). The interest rates will then show a broader spread than presently and well rated firms will profit from Basle II while badly rated firms will have to pay more or will possibly not receive a credit at all. The range of interest rates can be determined in dependence of the expected risk of failure.[1]

Although in frequent use, there exist very few studies that actually test for the information content of credit ratings. We report the results of a study that investigates the information value of the ratings by "Creditreform", the leading rating agency in Germany. In particular, we study whether the rating has explanatory power with respect to default of a firms in addition to publicly available information. "Publicly available information" means economic indicators of firm behavior and performance that are available without substantial cost to a possible lender who considers an investment. We compare two empirical models: The first explains the existence of a default in the next period by publicly available information like firm size, industry classification, productivity, firm age and business forecasts. In the second model, we add the rating of Creditreform to the specification. Hence we test whether the second model performs better than the first one regarding the regression fit. Given that the

[1] The special issue of the Journal of Banking and Finance (2001) deals with the new Basle Capital Accord in more detail.

main purpose of ratings is a prediction of firms reliability in the near future, we regard our empirical study as a test on the most important feature of credit ratings.

The literature on this topic is not very large. A related analysis is the one by Bongini, Laeven and Majnoni (2002). They compare the performance of credit ratings with publicly available information concerning the ability to forecast financial distress of banks in East Asia. According to their study publicly available information has some additional value aside of credit ratings. Ammer and Packer (2000) compare differences in default rates by sector and by ownership (U.S versus foreign firms). Controlling for credit rating and specific year influences, default rates appear to be higher for U.S. financial firms than U.S. industrial firms. However, they do not find significant differences in default rates between U.S. and foreign firms. Machauer and Weber (1998) as well as English and Nelson (1998) analyze how credit ratings affect the loan rate. Not surprisingly, the riskier the borrowers are rated, the higher are the paid interest rates. The factors determining the movement in out of financial distress are more frequently analyzed. See for recent examples, among others, Nickell, Perraudin and Varotti (2000) as well as Kaiser (2001).

Shumway (2001) uses a hazard rate model to forecast bankruptcy. He incorporates several different sets of independent variables including the well-known Altman (1968) and Zmijewksi (1984) models. Ratings are however not considered. A problem of his otherwise interesting study may be the sampling according to the value of the dependent variable (bankruptcy). Blume, Lim and MacKinlay (1998) compare the rating of corporate bonds from 1978 to 1995. They explain the rating by economic variables and find that the rating standards have become more stringent and not that the credit quality of U.S. firms has declined. Finally Dichev (1998) investigates whether firm distress measured by bankruptcy risk leads to higher returns, which would be the case if bankruptcy risk would be a systematic risk.

A closely related study to ours is that by Ewert and Szczesny (2001). They use a sample of 260 medium-sized firms over the periods 1992 to 1998. Among other things they explain the default of a firm by rating classes. These ratings in turn are individual ratings of six independent banks and therefore they have to construct a uniform rating system themselves (what we do not need to do). Another difference with respect to our study is, that Ewert and Szczesny have to oversample firms with financial stress, because with the limited number of observations, there would be not enough cases of defaults. We do not put into question the innovative study of Ewert and Szczesny (2001), but our sample has the advantage of a much larger size (71,479 and 79,290 versus 260 firms) and of being representative for manufacturing in Germany while Ewert and Szczesny cover only medium-sized firms. Moreover, we employ a uniformly constructed rating while Ewert and Szczesny use ratings stemming from six different institutions.

2 Theory

Ahead of giving a credit to a firm, for example, a lender will calculate the expected returns of the particular investment and will compare these with the returns of a risk-free investment. The lender has to estimate the probability of default for the former investment to compare both types of investment. We assume for illustration that with probability $0<P<1$ the credit is paid back to the lender. For simplicity, we assume that the credit has to be paid back within one period. As an alternative the lender can invest her/his money into a safe investment without risk with the interest rate i_0. The return is the credit plus the yield and therefore is equal to $(1+i_0)C$. The alternative is lending to a firm with a higher interest benefit i_1 (if $i_1>i_0$) in which case the expected return is

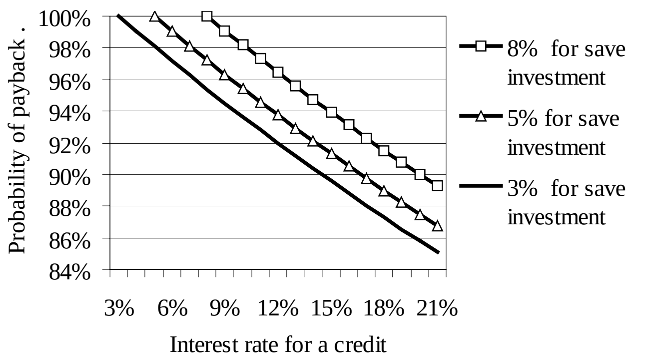
$$E(\pi)=P(1+i_1)C+(1-P)0 \tag{1}$$

The lender will choose the risky investment if the following condition holds:

$$P(1+i_1)C>(1+i_o)C \quad \Leftrightarrow \quad P>\frac{1+i_o}{1+i_1} \tag{2}$$

and will decide for the safe investment otherwise.[2] If, for example, i_0 is 3% and i_1 is 10%, the critical level of P would be 93,6%. Figure 1 shows for different interest rates for the safe investment that even for a rather high levels of P an investment into the firm in question would be often unattractive, because it would not be possible to charge the desired values of i_1 in practise (above the lines in Figure 1). It is important

Figure 1: Alternative Szenarios of i_o, i_1 and P



[2] Including operating costs for a bank or any other institution does not alter this result as long as the costs are a ratio of the credit or of the interest rate multiplied with the credit.

to note that a low rating by a credit rating agency does by no means imply P=0, but that the estimated repayment probability P may well be below the threshold defined by equation (2).

The lender will have several opportunities to collect information on P. She/he can use publicly available information like the general economic situation of the specific industry, firm size, firm age, labor productivity and perhaps other items. As an alternative or in addition one can use the rating of a professional agency. It is expected that such agencies have more or better information than is publicly and costlessly available.

3 Empirical Study

We compare the information value of credit ratings with publicly available information. The variable to be explained is a future default, that is a default in the following period. We use a one-year lead of the default, because according to the rating agency Creditreform the information contained in the ratings should be valid for about twelve month after their preparation. A default can have several reasons, like the inability to pay back a credit or in a worse case the bankruptcy and liquidation of a firm. Thus our dependent variable contains all the hazards which the lender wants to avoid by not giving a credit to such a firm. In case of a hazard, the dependent variable takes the value 1 and is zero otherwise.

The database contains Western German firms from all business sectors. The analysis considers only Western Germany, because the economic situation Eastern Germany is still different from the Western German one. On one hand, the Eastern German economy is still in transition from a planned economy to a market economy since the German Unification in 1990 and, on the other hand, the insolvency law has been different in the two parts of Germany until 1999. As recently as midyear 1999 there are no legal differences for insolvency in Eastern and Western Germany. At present we restrict our analysis to manufacturing industry in order to have roughly comparable firms and not to mix up specific circumstances in service industries with those in manufacturing industries. We employ cross-sectional data from 1999 and 2000 to check whether the regression results are robust over two different samples which are based on similar macroeconomic conditions. In 1999 (2000), the database contains 71,479 (79,290) observations on manufacturing firms - with defaults in only 1,828 (2,101) cases.

Our empirical test is based on the following methodology: The dependent variable is the existence of a default in the year t+1. The explanatory variables are taken from the period t, when the negative fact was not known. We estimate probit models and use two variants. Firstly, we include economically interesting and publicly available information in the regression. Secondly, we add the credit rating to the analysis and check if the fit of the regression improves.

As economically relevant and easily observable variables for a potential lender, we use firm size measured as logarithm of sales, ln(*SALES*), and firm age, ln(*AGE*). As a working hypothesis, we expect that larger and older firms are more firmly established than younger and smaller firms. It is well-known that a substantial proportion of newly founded firms gets bankrupt within a few years after foundation.[3] Another “standard” variable is the labor productivity measured as sales per employee, *SALES/EMP*. The productivity is specified as sales per employee as we have no information on value added and most likely the outside lender has also no information on value added, but about sales as well as about employment. Most likely will a higher productivity reduce the likelihood of a default. We also include a dummy that indicates whether firms have a liability limiting legal form. It is possible, that such firms follow a more aggressive firm policy in which case a default is more likely as the personal risk is reduced.[4] Moreover, we include the share of defaults in the previous period *t*-1 on a three digit industry level, because we think that this variable is a useful indicator for industry specific default risks. In addition, a general business forecast for *t*+1 on a two digit industry level (*FORECAST*) is applied. This indicator is called the "ifo Konjunkturindex" and is the most important business forecast in Germany finding broad attention in the public. However, it covers only the expectations from December concerning the following 6 months.[5] Nevertheless the business climate in a specific industry is expected to be valuable information for predicting the probability of default. Additionally, we use 17 industry dummies and seven state dummies for the Western German Länder[6] in order to take account of specific circumstances, that are related to industries and regions that are not covered by our main

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[3] For example, see discussions on the paradigms of the "liability of newness" and the "liability of adolescence" (cf. Singh et al., 1986, or Brüderl and Schüssler, 1990). Another frequently discussed factor for survival is entry size (see e.g. Agarwal and Audretsch, 2001, for a recent study).

[4] Cf. For an empirical study on the effects of limited liability for growth and survival Harhoff et al. (1998).

[5] Actually, the ifo Konjunkturindex is published quarterly, but we use only the one from December in period *t* covering the first half of the year *t*+1.

[6] Excluding Berlin. Smaller states were mergerd to one dummy: Bremen with Hamburg and Saarland with Rhineland-Palatinate

economic variables. In the second step of the analysis, we add the most important variable to the regressions: the credit rating. Creditreform uses several informations for its rating. These are in particular financial and liquidity risks and structural risks like industry classification, firm age, firm size and productivity, along with "soft factors" like payment history, volume of orders, firm development, management quality etc. On the basis of the individual facts Creditreform calculates a rating index ranging from 100 points to the maximum of 600 points. The worst firms receive 600 points and the best ones have 100 points. For their customers, the rating agency constructs a six-class rating (see Table 1):

Table 1: The Rating by Creditreform

Original Rating Classes of Creditrefrom	Credit Worthiness	Rating Index
1	very good	[100 – 130)
2	good	[130 – 200)
3	average	[200 – 300)
4	weak	[300 – 400)
5	not sufficient	[400 – 500)
6	turn away business connection	[500 – 600]

However, it turned out that the regression fit of the rating index is superior to dummy variables for the classes. Table 2 shows descriptive statistics of the variables.

Table 3 displays descriptive statistics for the percentage of defaults in the six rating classes. This simple comparison shows the strong differences between the rating classes. Surprisingly in the year 2000, in class 5 the probability of a default is higher than in class 6. Nevertheless according to these figures are the risks not evenly distributed over all classes. This already shows that the rating has a substantial explanatory power regarding future defaults.

Table 2: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.
		t = 1999 (*N* = 71,479)		
Dummy on default in *t*+1	0.0256	0.158	0	1.000
RATING INDEX/100	2.3938	0.714	1.000	6.000
ln(*SALES*)	14.5848	1.753	10.473	26.405
ln(*AGE*)	2.7205	1.116	0	6.512
Legal form dummy	0.6246	0.484	0	1.000
SALES/EMP	0.2434	0.173	0.034	3.043
FORECAST	-3.2545	17.123	-84.100	60.500
Share of defaults at the industry level (in *t*-1)	0.0268	0.008	0	0.125
		t = 2000 (*N* = 79,290)		
Dummy on default in *t*+1	0.0265	0.161	0	1.000
RATING INDEX/100	2.3680	0.685	1.000	6.000
ln(*SALES*)	14.3384	1.738	10.463	25.813
ln(*AGE*)	2.7678	1.093	0	6.544
Legal form dummy	0.6365	0.481	0	1.000
SALES/EMP	0.1908	0.152	0.034	3.000
FORECAST	2.1163	23.987	-103.000	98.400
Share of defaults at the industry level (in *t*-1)	0.0265	0.007	0	0.125

Table 3: Relationship between the rating in period *t* and a default in *t*+1

	Rating from 1999; default in 2000 absolute values *(row Percentages)*			**Rating from 2000 default in 2001:** absolute values *(row Percentages)*		
Rating Class:	No	Yes	Total	No	Yes	Total
1	526	2	528	595	2	597
	(99.62)	*(0.38)*	*(100.00)*	*(99.66)*	*(0.34)*	*(100.00)*
2	13,253	71	13,324	15,085	88	15,173
	(99.47)	*(0.53)*	*(100.00)*	*(99.42)*	*(0.58)*	*(100.00)*
3	50,527	476	51,003	56,327	609	56,936
	(99.07)	*(0.93)*	*(100.00)*	*(98.93)*	*(1.07)*	*(100.00)*
4	3,636	289	3,925	3,546	328	3,874
	(92.64)	*(7.36)*	*(100.00)*	*(91.53)*	*(8.47)*	*(100.00)*
5	459	227	686	423	294	717
	(66.91)	*(33.09)*	*(100.00)*	*(59.00)*	*(41.00)*	*(100.00)*
6	1,250	763	2,013	1,213	780	1,993
	(62.10)	*(37.90)*	*(100.00)*	*(60.86)*	*(39.14)*	*(100.00)*
Total	69,651	1,828	71,479	77,189	2,101	79,290
	(97.44)	*(2.56)*	*(100.00)*	*(97.35)*	*(2.65)*	*(100.00)*

Based on Table 3 and referring to the theoretical model in Section 2, one can calculate critical interest rates for a given rating, where an investor would be indifferent between a save investment and a firm investment. Let us consider a rating of class 3: the empirical default probability is around 1% in both years. If a save investment would be available at an interest rate of i_0 = 3%, a potential investor would be willing to give a credit to a firm if i_1 > 4.04% (see equation 2). For the better rating classes 2 and 1, the critical interest rate converges to the interest rate of the safe investment option. However, if a firm has a weak rating of class 4, the paypack probability declines significantly to 92.6% in 1999 and thus i_1 would have to be 11.2% in 1999 to receive a credit. For firms in class 5 and 6 it would be virtually impossible to get a credit.

In the following, we run Probit regression for both the sample from 1999 and 2000 to answer the question whether the rating index outperforms several other variables in forecasting a default in a multivariate context. As said above, we start with economically interesting variables, which are available to the public, to estimate the default risk.. Then we add the credit rating, *RATING INDEX* (divided by 100), as well as polynomials of the rating in further regressions [*(RATING INDEX/100)* ^{2} and *(RATING INDEX/100)* ^{3}].

In empirical studies like this heteroscedasticity is frequently a problem. Although this is in many cases ignored, heteroscedasticity may have very undesirable effects for the estimation of Probit models, that is, inconsistent parameter estimates. We test for the existence of heteroscedasticity and carry out Probit estimations with heteroscedasticity taken into account. We consider groupwise heteroscedasticity modeled by the 17 industry dummies and seven size dummies constructed by the firms' number of employees (cf. Greene, 2000, pp. 829-31, for technical details). The results are presented in Table 4 for 1999 and Table 5 for 2000. As the likelihood ratio statistics indicate, homoscedasticity is rejected in all models considered.

Table 4: Probit Models on a Default – Sample from 1999 (71,479 observations) [a)]

Dependent Variable: Dummy on default in t+1 (t = 1999)								
	Homoscedastic Models				Heteroscedastic Models [b)]			
Variable	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
RATING INDEX/100		0.673 ***	1.3533 ***	-1.076 ***		0.708 ***	1.641 ***	-1.024 ***
		(0.010)	(0.074)	(0.314)		(0.032)	(0.120)	(0.379)
(RATING INDEX/100) ^{2}			-0.086 ***	0.590 ***			-0.113 ***	0.609 ***
			(0.009)	(0.085)			(0.013)	(0.104)
(RATING INDEX/100) ^{3}				-0.058 ***				-0.061 ***
				(0.007)				(0.009)
ln(*SALES*)	-0.074 ***	0.077 ***	0.090 ***	0.075 ***	-0.268 ***	0.062 ***	0.023	0.037 *
	(0.009)	(0.010)	(0.010)	(0.010)	(0.034)	(0.019)	(0.020)	(0.020)
ln(*AGE*)	-0.146 ***	-0.052 ***	-0.037 ***	-0.049 ***	-0.199 ***	-0.064 ***	-0.054 ***	-0.064 ***
	(0.010)	(0.012)	(0.012)	(0.012)	(0.019)	(0.013)	(0.014)	(0.014)
Legal form dummy	0.052 **	0.070 **	0.047	0.072 **	0.061 *	0.060 *	0.038	0.059 *
	(0.024)	(0.030)	(0.030)	(0.030)	(0.032)	(0.032)	(0.034)	(0.033)
SALES/EMP	-0.657 ***	-0.552 ***	-0.537 ***	-0.536 ***	-0.211	-0.495 ***	-0.304 **	-0.399 ***
	(0.088)	(0.099)	(0.100)	(0.100)	(0.139)	(0.117)	(0.124)	(0.123)
FORECAST	-0.001	-0.001	-0.001	-0.001	-0.0002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of defaults at the	6.007 ***	4.799 ***	4.777 **	4.813 ***	8.359 ***	5.218 ***	5.551 ***	5.365 **
industry level (in t-1)	(1.560)	(1.863)	(1.882)	(1.887)	(2.256)	(2.000)	(2.160)	(2.117)
Constant term	-0.586 ***	-0.973 ***	-1.354 ***	-1.230 ***	1.894 ***	-0.724 ***	-0.479 *	-0.701 ***
	(0.133)	(0.151)	(0.158)	(0.159)	(0.452)	(0.251)	(0.270)	(0.266)
17 industry dummies [c)]	32.65 **	26.21 *	28.44 **	29.62 **	18.08	12.51	12.10	11.64
7 state dummies [c)]	39.12 ***	57.37 ***	71.66 ***	62.11 ***	33.77 ***	52.23 ***	63.01 ***	55.47 ***
Log-Likelihood	-8116.847	-5813.598	-5770.582	-5741.518	-8073.304	-5793.775	-5741.492	-5718.212
LR-Test on Heteroscedasticity: $\chi^2(23)$	-	-	-	-	46.51 ***	39.65 **	58.18 ***	46.61 ***
McFadden R^2	0.0458	0.3165	0.3216	0.3250	0.0509	0.3189	0.3250	0.3278
Veall-Zimmerman R^2	0.0561	0.3644	0.3698	0.3735	0.0623	0.3669	0.3735	0.3764

a) Standard errors in parentheses. *** (**,*) denote a significance level of 1% (5, 10%).

b) Heteroscedasticity is modeled groupwise as $\sigma_i = \sigma \exp(w_i{}'\alpha)$ where w_i' includes 7 size dummies and 17 industry dummies.

c) Chi-squared statistic on joint significance.

Table 5: Probit Models on a Default – Sample from 2000 (79,290 observations) [a)]

Variable	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
	Dependent Variable: Dummy on default in t+1 (t = 2000)							
	Homoscedastic Models				Heteroscedastic Models [b)]			
RATING INDEX/100		0.692 ***	1.479 ***	-0.761 ***		0.696 ***	1.561 ***	-0.981 ***
		(0.010)	(0.070)	(0.298)		(0.032)	(0.105)	(0.325)
(RATING INDEX/100) ^{2}			-0.101 ***	0.525 ***			-0.109 ***	0.591 ***
			(0.009)	(0.082)			(0.011)	(0.091)
(RATING INDEX/100) ^{3}				-0.054 ***				-0.060 ***
				(0.007)				(0.008)
ln(*SALES*)	-0.046 ***	0.096 ***	0.113 ***	0.098 ***	-0.087 ***	0.127 ***	0.099 ***	0.107 ***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.022)	(0.015)	(0.016)	(0.016)
ln(*AGE*)	-0.159 ***	-0.068 ***	-0.051 ***	-0.061 ***	-0.158 ***	-0.068 ***	-0.057 ***	-0.067 ***
	(0.009)	(0.011)	(0.011)	(0.011)	(0.020)	(0.012)	(0.012)	(0.012)
Legal form dummy	0.017	0.055 **	0.024	0.049 *	0.019	0.044	0.015	0.037
	(0.023)	(0.028)	(0.028)	(0.028)	(0.023)	(0.028)	(0.029)	(0.029)
SALES/EMP	-0.451 ***	-0.591 ***	-0.581 ***	-0.564 ***	-0.280 ***	-0.709 ***	-0.507 ***	-0.587 ***
	(0.088)	(0.105)	(0.106)	(0.106)	(0.108)	(0.118)	(0.121)	(0.121)
FORECAST	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of defaults at the industry level (in t-1)	7.493 ***	5.043 ***	4.884 ***	5.161 ***	8.192 ***	5.067 ***	5.045 ***	5.233 ***
	(1.569)	(1.836)	(1.857)	(1.860)	(1.874)	(1.842)	(1.942)	(1.923)
Constant term	-0.962 ***	-0.984 ***	-1.479 ***	-1.374 ***	-0.506 *	-1.336 ***	-1.289 ***	-1.449 ***
	(0.121)	(0.138)	(0.146)	(0.147)	(0.292)	(0.198)	(0.209)	(0.207)
17 industry dummies [c)]	21.78	22.15	25.02 *	21.84	36.45 ***	19.32	17.93	20.36
7 state dummies [c)]	59.56 ***	81.79 ***	101.92 ***	72.02 ***	37.87 ***	73.93 ***	88.13 ***	78.50 ***
Log-Likelihood	-9342.083	-6725.572	-6660.365	-6632.781	-9313.129	-6702.922	-6639.532	-6610.283
LR-Test on Heteroscedasticity: $\chi^2(23)$	-	-	-	-	57.91 ***	45.30 ***	41.67 ***	45.00 ***
McFadden R^2	0.0370	0.3067	0.3134	0.3163	0.0400	0.3091	0.3156	0.3186
Veall-Zimmerman R^2	0.0456	0.3551	0.3623	0.3654	0.0493	0.3576	0.3646	0.3679

a) Standard errors in parentheses. *** (**,*) denote a significance level of 1% (5, 10%).

b) Heteroscedasticity is modeled groupwise as $\sigma_i = \sigma \exp(w_i{}'\alpha)$ where w_i' includes 7 size dummies and 17 industry dummies.

c) Chi-squared statistic on joint significance.

The impact of the rating is always significantly different from zero and the coefficients have the expected sign. The higher (worse) the rating, the higher is the predicted default risk. The improvement of the models when the ratings are added is large: McFadden's R^2 becomes about seven times higher in 1999 and more than eight times higher in 2000.[7] We also report the Veall-Zimmermann-R^2, because this measure of goodness-of-fit is closer related to the OLS-R^2 than Mc-Fadden's R^2 (see Veall and Zimmermann, 1996, for a discussion on different Pseudo-R^2 in limited dependent variable models).[8] However, there are no substantial changes in the interpretation. The Veall-Zimmermann-R^2 are somewhat larger than the McFadden's R^2 but the differences between the models based only on usual economic indicator and the models including the ratings remain very large. On the basis of these results, we conclude that Creditreform makes a good job. The classification is valuable information superior to easily observable variables.

The share of previous defaults at the industry level is always highly signficant in the regressions. This points either to industry differences of entry and exit cost or to structural problems in certain declining industries. Interestingly, the general business forecast is insignificant in all regressions. One reason may be that this forecast is aimed on the development macroeconomic business cycle, but of course not on microeconomic defaults. Another explanation is that *FORECAST* is just very well included in the rating along with other much more detailed knowledge about the specific firm and, hence, has no remaining explanatory power. ln(*AGE*) has the expected negative sign in the regressions and is significant in all cases. Young firms are more likely to a default than more established ones. Moreover, the productivity measured by *SALES/EMP* is negatively significant in all models. Of course, the lower the productivity the more probable is a default.

However, a puzzle remains: In Models I and V, the firm size measured by sales has the expected negative impact on the probability of a default in t+1, but once the credit rating is included in the regressions, the sign of ln(*SALES*) becomes positively significant. This fact is true in both analyzed years in the homoscedastic as well as in the heteroscedastic case.

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[7] The McFadden R^2 is often called likelihood ratio index (*LRI*) and is defined as $1-\ln L_1/\ln L_0$ with $\ln L_0$ being the log likelihood if only a constant term is included in the model in contrast to $\ln L$ as the maximized value of the log-likelihood function.

[8] The Veall-Zimmermann R^2 is defined as $(d-1)/(d-LRI)LRI$ with $d=n/(2\ln L_0)$ where n is the number of obervations.

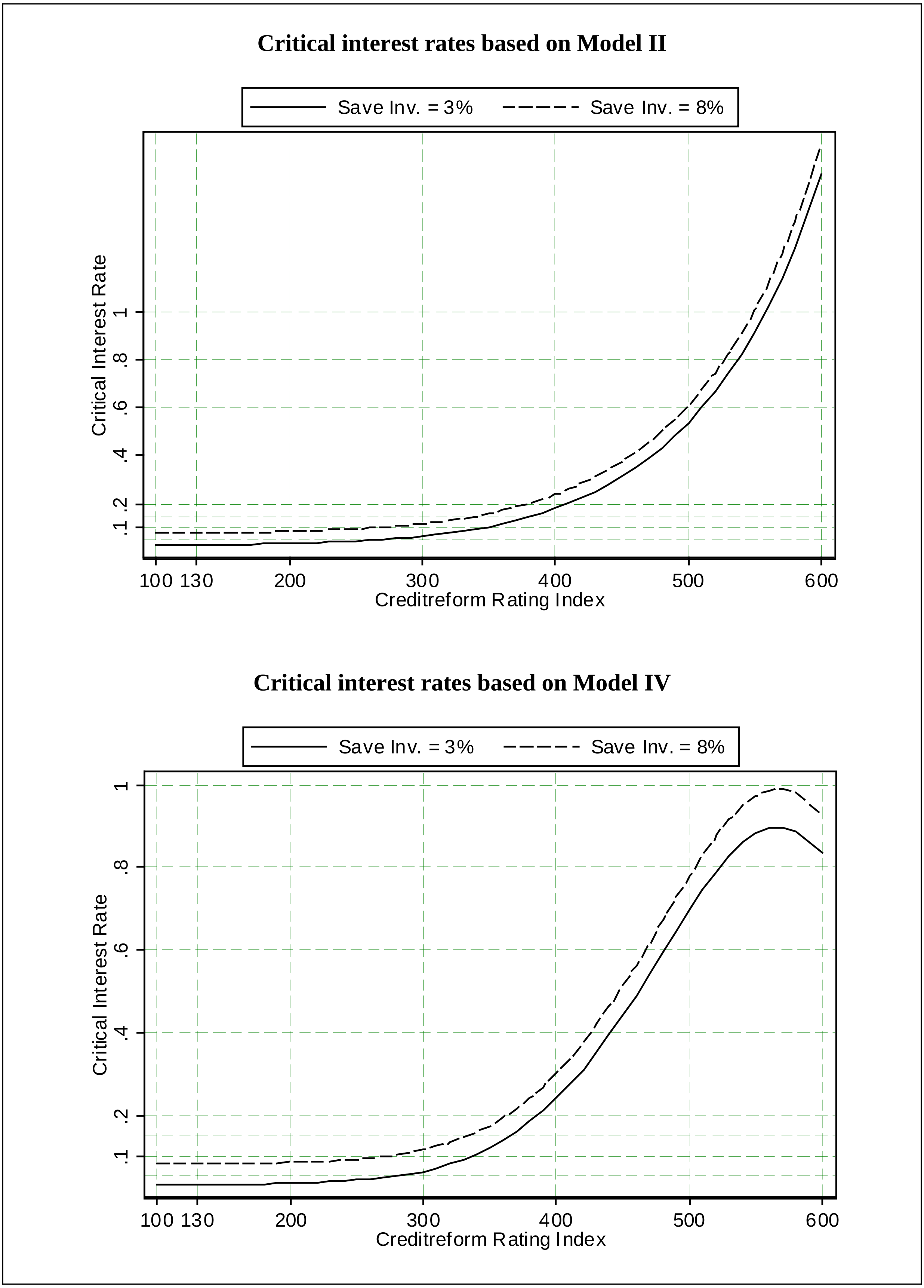
Therefore, we conclude that the rating agency overemphasizes the factor firm size in its construction of the rating index.

Krahnen and Weber (2001) discuss requirements of an ideal rating system. One criterion is that ratings should be informationally efficient, that is, all available information should be modeled correctly in the rating. Informationally efficient is here defined in the following way: "As mentioned before, a rating system should correctly incorporate all information available to the bank, both public and private, i.e. it should be efficient." If this requirement has to be tested, it has to be tested, whether the publicly available information has any additional explanatory power aside of the rating system. As our results show most of the other control variables remain highly significant in the regressions even when polynomials of the rating are included. According to this result, the Creditreform rating system is not informationally efficient, because the publicly available information has some additional explanatory value.

Finally, we can again refer to the theoretical model presented in Section 2 and calculate critical interest rates for a firm investment on basis of the Probit estimates. For this illustration, we use the estimates from 1999 and compute the payback probabilities for different ratings of a hypothetical average firm, i.e. we use the mean values of all explanatory variables except the rating. The payback probability for the average firm is simulated for all possible values of the rating index and the critical value if i_1 is computed according to equation 2. Figure 2 displays the critical interest rates based on the linear specification in Model II and the cubic specification in Model IV. If firms have a good rating, the risk premium for a firm investment is low, but once a firms receives a weak rating the threshold value of the interest rate i_1 increases dramatically. For example, if an "average firm" is rated in class 4, with a rating index of 350 (see Table 1), and a save investment is available with 3% return, the interest rate for a credit has to be at least 9.5% to convince a potential investor (according to Model II).[9] As the graph of the cubic model illustrates the fit of the curve is not perfectly accurate at the right-hand side. The interest rates should not decrease for the worst ratings. However, for the interpretation of the results this inaccuracy of the parametric specification is not relevant, because the critical value of the interest rate i_1 is already well above every realizable magnitude.

[9] According to Model IV the interest rate would already be 12%.

Figure 2: Critical Interest Rates based on the Probit Estimates from 1999



It becomes obvious that the introduction of rating based credit allocation will lead to a much larger spread of interest rates than it is usual nowadays. While the risk premium is low for the majority of firms, it will yield high costs for the about 10% of firms with weak and worse ratings. Especially small firms and start-ups will have difficulties to raise external capital.

4 Conclusion

We present results on an important question, namely whether credit rating is really able to predict defaults in a better way than publicly available information. On the background of the New Basle Captial Accord (Basle II agreement) the importance of such ratings will most likely increase in the future and therefore such empirical research is valuable.

We report the results of an empirical study on the value of credit rating for explaining future defaults. Basically two models are compared, the model with economically meaningful variables that are publicly available versus a model with the credit rating added to the other variables. We also estimate variations of the model including the rating, in particular with non-linear impact of the rating index. It turns out that the full model is much better than the simpler ones without the rating. Therefore, we conclude that a credit rating has additional information value for lenders.

However the publicly available information has an independent power aside of the ratings of Creditreform. Therefore in a strict version of the notion "informationally efficient" the ratings are inefficient. Another puzzle is the result: the firm size has the expected negative sign in the model without the rating, but once the credit rating is included in the regressions, firm size becomes positively significant. Thus, we conclude that the rating agency overemphasizes the factor firm size in its construction of the rating index.

On the basis of a simple theoretical model, we compare an investment into a safe loan with a risky credit for which a positive default probability exists. In particular, for different ratings the expected default probabilities are calculated and based on these the critical interest rates are determined which are necessary to cover the expected losses and yield in addition the return from a safe investment. In the cases of the two worst rating categories the default probability is so high that no reasonable interest rate can compensate for the risk of loss of the whole credit. However, even a rating in the third worst category (4 out of the range 1-6) is associated with an interest rate of 9.5% in comparison to a save return of 3% if both investments are required to yield the same expected return. Hence if in line with the New

Basle Capital accord risk is accurately taken into account, the interest spread will be much more pronounced than it is currently the case.

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