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Determinants of Bank Lending Performance*

Ralf Ewert und Gerald Schenk#

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Abstract: During the last years the lending business has come under considerable competitive pressure and bank managers often express concern regarding its profitability vis-a-vis other activities. This paper tries to empirically identify factors that are able to explain the financial performance of bank lending activities. The analysis is based on the CFS-data-set that has been collected in 1997 from 200 medium-sized firms. Two regressions are performed: The first is directed towards relationships between the interest rate premiums and various determining factors, the second aims at detecting relationships between those factors and the occurrence of several types of problems during the course of a credit engagement. Furthermore, the results of both regressions are used to test theoretical hypotheses regarding the impact of certain parameters on credit terms and distress probabilities. The findings are somewhat “puzzling“: First, the rating is not as significant as expected. Second, credit contracts seem to be priced lower for situations with greater risks. Finally, the results do not fully support any of three hypotheses that are often advanced to describe the role of collateral and covenants in credit contracts.

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Johann Wolfgang Goethe-University, Frankfurt/M., Faculty of Economics Department of Controlling, Mertonstr. 17, D-60054 Frankfurt am Main, e-mail: ewert@em.uni-frankfurt.de, G.Schenk@em.uni-frankfurt.de

1. Introduction

This paper is part of a comprehensive research project on „credit policy" intitiated by the „Center for Financial Studies" (CFS) of the Johann Wolfgang Goethe-University of Frankfurt/M. The starting point for our part is as follows: In discussions with bankers it is often advanced that the „traditional" credit business has come under considerable competitive pressure. Thus, credit margins are said to decrease and the profitability of lending becomes doubtful. In banks with several lines of business (e.g. German universal banks offering virtually all types of financial services), granting credit to a firm seems more to be viewed as a „door opener" for other transactions (e.g. investment banking activities etc.) that are hypothesized to be more advantageous for the bank. Thus, arguments of „cross selling" are often deemed to be major factors in support of the lending business.

Regarding the discussion described above it is an interesting question to study the empirical determinants of bank lending performance. Are there any empirical regularities between several factors and measures for the „success" of the lending business? Answering that question could not only yield insights regarding the empirical validity of theories that try to explain reality; it could also help practitioners seeking for alternatives to improve the profitability of their credit transactions.

Conceptually the preferred way to measure „success" in economic terms is looking at the incremental cash flows resulting from a lending contract. Thus, in order to detect any relations between determining factors and cash-flow-based success indicators, the following procedure seems to be suitable: First, the cash flows that really occurred from a sample of credit contracts could be represented by a single indicator for each respective element, e.g. the internal rate of return. Then the internal rates of return for the sample could be regressed on various factors that are hypothesized to impact on the cash flows and, therefore, on the profitability of a lending contract. However, when we tried to employ this procedure we encountered severe problems of data availability regarding the real cash flows of completed credit contracts. For that reason it was impossible to use a purely cash-flow-based approach. Therefore, we applied two alternative measures that serve as proxies for the success in cash flow terms:

- The first measure (explained in more detail in section 2 below) is based on the idea that a loan contract´s profit emerges from an *interest rate premium* over a rate that the funds could have alternatively been invested at. Hence, it is a rough measure of the *surplus* the bank could reap if there are no problems during the life of the credit contract.
- The second measure captures such potential problems by looking at the frequency by which „disturbances“ (e.g., delay of principal and/or interest payments by the borrower, technical default by the borrower or even insolvency etc.) occurred. Such disturbances imply either a definitve loss of payments for the bank or additional costs due to renegotiations, active involvement in the borrower´s firm policy and/or use of collateral etc.). Thus, the higher the frequency of such disturbances the lower the profitability of a credit contract.

Our paper is linked with the recent literature on relationship banking[1]. It contributes to that literature in several ways: Concerning the „surplus“-question it augments the existing literature by studying a different sample of data stemming from German banks. We were allowed to use confidential data contained in the respective bank´s credit evaluation files. This enables the use of various measures (e.g., the bank´s rating of a borrower etc.) that are somewhat different from (and more comprehensive as) traditional financial accounting measures. Furthermore our study tries to incorporate aspects like „cross selling“ and „intensity of competition“ as independent variables for the „surplus question“. Third, the „disturbance“ question has up to now - according to our knowledge - not been pursued in the relationship banking literature. We study this question by using methods of logistic regression and incorporating not only data from financial statements but also from the individual credit contracts. Furthermore the results of the logistic regression analysis may additionally be used as a basis for classification purposes. Finally, combining the results of our two regressions we are able to test several hypotheses regarding the use of credit contract variables (i.e., collateral and bonding).

In our study we use the common data set for the CFS research project on „credit policy“. The sample selection procedure as well as some descriptive statistics have been described in *Elsas et al.* (1997). We refer to that paper for all basic information (sampling procedures, descriptive statistics, etc.) regarding the data. The current paper concentrates on the use of

[1] See for example *Petersen/Rajan* (1994), *Berger/Udell* (1995) and *Blackwell/Winters* (1997).

the raw data and contains additional data descriptions only when necessary for the specific research questions at hand.

The remainder of the paper is organized as follows: Section 2 is devoted to the „surplus“ question. We first consider the independent variables and possible theoretical arguments about the impact these variables should have on the interest rate premium. Then we present the results of an OLS-regression and give some interpretations. Section 3 concentrates on the „disturbance“ question. Again we first describe independent variables and conceptual arguments regarding the respective consequences for the frequency of potential problems. Then the results of a logistic regression are presented and interpreted. Finally we show how these results could be used for classification of firms in „problem“ and „no-problem“ categories by *explicitly considering possible relations between the two types of misclassification costs*. Section 4 contains a short summary of the findings and concludes with some suggestions for future research.

2. Surplus question

In this chapter we study the effects of different determinants on the pricing of *credits in current account*[2]. The spread between the interest rate of the loan and the respective (3-months) Frankfurt interbank offered rate (FIBOR) is chosen to be the dependent variable of our OLS-regression[3]. This interest rate premium (*IRP*) is regressed on firm and credit variables as well as on additional control variables for possible industry, bank, and year effects. In subsection 2.1 the independent variables used in our regression are presented in detail.

2.1. Variables

2.1.1. Firm variables

To control for firm-specific characteristics a set of „firm variables“ was chosen. Since the data set of the „CFS“-sample is based on direct access to the bank´s credit evaluation files we especially had the unique opportunity to use the individual rating of a firm. This rating variable is augmented by some „traditional“ financial variables usually employed to characterize the financial condition of a firm.

Rating (RAT): The rating reflects the bank's individual evaluation of the loan's risk and is essentially a compact and comprehensive measure of various quantitative and qualitative factors (e.g., the quality of the management, the market position of the firm and its future prospects etc.). Therefore, the rating should be expected to be a very important determinant of the *IRP*. The different internal rating systems of the five banks participating in our project do not allow a homogenous assessment of the quality of the borrowers in the entire data

[2] We concentrate on the results for these types of credit because they allowed for a relatively straightforward standardization of benchmark interest rates. However, the results for the sample of investment credits using the margins documented in the respective credit contratcs (the comparability of which is somewhat problematical due to different procedures of banks with respect to benchmark rates, cost assessment etc.) do not qualitatively differ from those of credits in current account. Interested readers may obtain further information from the authors upon request.

[3] More precisely: The FIBOR-rate for a loan was computed by taking the monthly FIBOR-average for the month that the credit was granted to the respective firm.

record. Therefore we had to transform the individual rating systems into a uniform scheme.[4] The resulting classification scheme is shown in table 1:

Rating category	Credit standing
1	very good
2	good, above average
3	average
4	below average
5	problematic borrower
6	loan in danger; loss of loan

Table 1: Transformed rating system

The rating is integrated in the OLS-regression by means of dummy variables. We hypothesize: The higher the rating category the higher the *IRP*.

Equity ratio (ER): Theoretical models of capital structure[5] predict that the default probability of firms with a low equity ratio[6] is - ceteris paribus - higher than the default probability of firms with high a equity ratio. If this higher default probability is reflected in the interest rate, we should expect a negative relation between the equity ratio and our dependent variable.

Return on total assets (RT): The return on total assets variable (defined as the ratio of the firm´s earnings to the balance sheet total) is a rough measure for the earning power and the profitability of a firm and should therefore be positively related to the repayment probability of a loan. It is hypothesized that the *IRP* of a loan decreases with higher returns on total assets.

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[4] The rating systems of the five banks and the transformation mechanism are described in detail in *Elsas et al.* (1997).
[5] See, e.g., *Kraus/Litzenberger* (1973).
[6] For purposes of this study the equity ratio was defined as the ratio of book value of equity to the balance sheet total.

Size: In previous empirical studies[7] firm size often proved to be a significant variable with a negative impact on interest rates. To control for such possible size effects we include Ln(sales) as a measure for firm size.

Because the rating basically incorporates various firm characteristics we do not include more variables to describe the situation of a firm. This procedure seems also to be justified by looking at the results of the prevailing studies mentioned above, where the sometimes numerous factors employed to define the specific situation of a firm were largely insignificant (except firm size)[8].

2.1.2. Credit variables

To characterize the credit environment the following credit variables are used:

Collateral (UNCOL) and Covenants (COV): Credit contracts often contain requirements for the borrower to provide collateral and to comply with various covenants. While other papers integrated collateral requirements by means of dummy variables[9] (e.g., 1 if collateral is pledged, 0 if the loan is unsecured), we had the opportunity to incorporate collateral in a more detailed form due to the access to the banks´ credit files. We represent collateral requirements by that proportion of the loan that is uncollateralized (UNCOL). Regarding covenants we used a dummy (COV) to account for the existence of such provisions (e.g., direct and/or indirect dividend constraints[10], etc.).

The hypotheses regarding the impact these variables on the *IRP* depend on the theoretical framework. Using arguments stemming from *combining agency- and signaling-theory* better firms can signal their true quality by offering more collateral and/or restrictions (covenants) to bondholders[11]. Better firms know that they will not severely suffer from offering more collateral and/or covenants because of their relatively low probability for the occurrence of situations where covenants are violated and/or the bank might use the pledged assets. Thus, it pays for better firms to offer more collateral and/or covenants in exchange for lower interest rates. According to this theory a negative relationship should

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[7] *Petersen/Rajan* (1994), *Blackwell/Winters* (1997).
[8] This is especially true for the studies of *Berger/Udell* (1995) and *Blackwell/Winters* (1997).
[9] This is the procedure employed in *Berger/Udell* (1995) and *Blackwell/Winters* (1997).
[10] See for a conceptual analysis of the efficacy of such constraints *John/Kalay* (1982), *Kalay* (1982), *Ewert* (1986), (1987), *Berkovitch/Kim* (1990) and *Leuz* (1996).

hold between the amount of collateral and/or the existence of covenants and the *IRP*; that amounts to a positive (negative) coefficient for UNCOL (COV).

A converse view is often advanced by practitioners and amounts to a „*reverse signaling argument*“. According to that view banks only require collateral and/or covenants for relatively risky firms.[12] If the firm is instead classified as having only low risk the bank dispenses with collateral and/or covenants. Thus a positive relationship should hold between the amount of collateral and/or the existence of covenants and the *IRP*, which implies a negative (positive) coefficient for UNCOL (COV).

If instead *pure financial contracting theory*[13] is used the resulting impact is only clear for the individual firm but not in a cross-sectional analysis. According to this theory lenders are able to form rational and unbiased expectations regarding the firm´s future prospects. There are firm-specific agency-problems that can be mitigated by the use of collateral and/or covenants. Each firm chooses a specially designed credit contract that maximizes firm value by trading off additional monitoring and bonding costs against reductions in interest rate premiums. For a single firm the use of collateral and/or covenants should reduce credit costs, which amounts to a negative relationship between these variables. However, in a cross-section that relationship need not hold because usually the firms with the highest degree of agency problems (which presumably are high risk firms) will find it most advantageous to offer credit contracts including collateral and/or covenants. Thus, it may well be that there is *cross-sectionally* a positive relationship between the observed *IRP* and the use of collateral and/or covenants, depending on which of the two effects (reduction of individual credit risks versus use of collateral and/or covenants by observably riskier firms) is stronger.

Summarizing the above discussion, only the signaling and reverse-signaling hypotheses yield clear implications for the sign of the coefficients of UNCOL and COV. In any case the results of *both regressions* (i.e., „surplus“ and „disturbance“ question) have to be considered in testing the respective theories, since the Logit-analysis for the „disturbance“-question is a direct test of the relationship between several determining factors and the

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[11] See for different contexts of such explanations e.g. *Bester* (1985, 1987), *Chan/Kanatas* (1985), *John/Kalay* (1985), *Besanko/Thakor* (1987) and *Ewert* (1988).
[12] Some theoretical justification for this view is given by *Bester* (1994).
[13] See, for example, *Jensen/Meckling* (1976), *Myers* (1977) and *Smith/Warner* (1979).

observed probability of problems. Thus, the Logit results may corroborate or contradict the results of the premium-regression.

Cross selling (CS): As mentioned in the introduction, the lending business seems to be often viewed just as a door opener for other transactions. To account for such aspects we used a dummy variable that was coded 1 if cross selling arguments were explicitly found in the bank´s loan files and 0 otherwise. We expect that the existence of cross selling arguments should go along with a lower *IRP*.

Intensity of competition (HHI): In order to include the intensity of competition between bank institutions in our regression analysis we use the so called „Hirschmann-Herfindahl Index" (*HHI*) with the modification of *Riekeberg* (1995). This index is designed to measure the concentration of bank institutions in the area where the borrowing firm is headquartered. The *HHI*-index is calculated as follows:

$$HHI = \frac{\sum_{i=1}^{n} \left(NBO_i \right)^2}{\left(\sum_{i=1}^{n} NBO_i \right)^2}$$

NBO_i refers to the number of branch offices bank *i* has in the respective regional bank market. The first three digits of the German five-digit-postal-district-code-numbers were used for the demarcation of the regional bank markets. The numbers of branch offices in these markets were taken from the branch office statistic of the „Deutsche Bundesbank". As the HHI - index *increases with decreasing intensity of competition* (as measured above) we should expect the coefficients of the HHI - index to have a positive sign.

House bank relationship (HB): The closeness of the relationship between the firm and the bank is often designated as a very important factor for the pricing of loans[14]. Most former studies use the duration of the relation between the firm and the bank as a measure for the closeness of that relationship. In our project we had the opportunity to directly inspect the respective loan files and to ask the banks officials about their evaluation. To account for possible house bank aspects we incorporate a dummy coded 1 if the bank itself marked the relationship a house bank relationship and 0 otherwise[15]. The usual hypothesis

[14] Theoretical arguments can be found, for example, in *Diamond* (1989) and *Diamond* (1991).
[15] See for a more detailed procedure concerning the housebank definition *Elsas/Krahnen* (1998).

is, that close relationships between banks and lenders are valuable and should lead to a decrease in the *IRP*.

Number of banks (NUM): On the one hand, the number of banks which a firm borrows from can be viewed as a proxy for the closeness of the relationship between the bank and the borrower. On the other hand, it can also be viewed as a measure for the quality of the borrower. The lower the quality of a firm the more the firm has to seek for banks who agree to give additional credits. Both arguments predict a positive relation between the number of banks and the *IRP*.[16]

Bank´s credit as a portion of the firm´s total capital (BCP): Another variable we examine is the firm's total available credit from the bank as a percentage of the firms total assets (BCP). Two competing theories concerning this variable are possible. On the one hand, this variable may be viewed as another proxy for the closeness of the relationship between the bank and the borrower. According to this view, a high BCP means that the relationship is relatively close[17] and one should observe a negative relation between the BCP and the *IRP*. On the other hand, a high BCP also implies that the bank bears a higher risk of the borrower´s investment program. Using this argument one should expect a positive relation between the BCP and the *IRP* due to a greater risk premium. The net effect resulting from both arguments is open.

2.1.3. Additional control variables

Industry dummies: Industry characteristics are included in our regression analysis because they also can affect a loan´s risk. Different branches are reflected in dummy variables. We differentiate between the manufacturing sector, the construction sector, the service sector, the distribution sector, and other industry sectors[18].

Bank dummies: In order to identify whether banks use different proceedings in the pricing of loans and/or whether the chosen variables have different influences in different banks, we also include the five banks participating in our research project by dummy variables.

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[16] *Petersen/Rajan* (1994) empirically document such an relationship.
[17] See for a similar argument *Blackwell/Winters* (1997), p. 279.
[18] Most of the firms in this category were in the food and beverage industry.

Year dummies: The CFS-sample covers a time period of five years (1992-1996). Thus, it also seems to be necessary to control for different years of lending. Among other things, the significance of year dummy variables would suggest that the lending policy of banks was also influenced by economy-wide factors.

2.2 Results

Table 2: OLS-regression of the *IRP* for sample A (N = 299) and sample B (N = 141) of the CFS-data-set. For the categorial dummies rating, bank, industry and year the basis is indicated respectively. With regard to the rating, RAT1 and RAT2 have been grouped together. Following the discussion above the predicted signs (if possible) of the coefficients for the firm- and credit-variables are given in parentheses.

Variables	Sample A	Sample B
Intercept	4.483*	3.0858*
Firm variables (Rating dummies relative to RAT1,2)		
RAT3 (+)	.1839	-.2729
RAT4 (+)	.1895	.1993
RAT5 (+)	.5168**	.1635
RAT6 (+)	#	.564
ER (-)	-.0043***	.005
RT (-)	.0007	.0086
LNSALES (-)	-.1503*	-.1369***
Credit variables		
UNCOL (?)	-.0041**	-.007*
COV (?)	.2824**	.0544
CS (-)	-.2126**	.0099
HHI (+)	-1.8998*	2.6372*
HB (-)	-.1579	-.2545
NUM (+)	.1389	.0241
BCP (?)	-.4233	0.0086
Industry dummies (Relative to the manufactoring sector)		
Construction sector	.2415	#
Service sector	.4818**	-.1682
Trade sector	-0.0364	-.3643
Other sectors	-.1056	-1.1236*
Bank dummies (Relative to Bank 1)		
Bank 2	-.1479	.2202
Bank 3	.3549**	1.1989*
Bank 4	.0923	.3355
Bank 5	.2124	-.0625
Year dummies (Relative to 1992)	Sample A (N = 299)	Sample B (N = 141)
1993	1.3854*	1.4711*
1994	1.7266*	2.0623*
1995	1.7764*	2.1897*
1996	2.0041*	2.7309*
Adjusted R^2	.5667	.6552
F-statistic	16.6065*	11.6412*

* Significant at the 1 percent level.
** Significant at the 5 percent level.
*** Significant at the 10 percent level.

No case with this characteristic found.

The regression has good explanatory power according to the usual measures. In the sequel the results are discussed for the respective groups of variables.

2.2.1 Firm variables

The results concerning the *rating variables* are somewhat surprising. Taking into account that the rating essentially condenses plenty of information of various sources and origins, one should expect strongly significant positive coefficients for all rating dummies increasing in the rating number. The results, however, show that the rating variables are largely insignificant except the coefficient for RAT5 in sample A. Moreover, the monotonicity property is violated in sample B, and RAT3 in that sample even has a negative coefficient. Hence, a systematic and significant relationship between the rating and the interest rate premium - given all other variables - cannot be detected.

This result is not easy to explain, but some possible hypotheses can be given. First, one could argue that there are other factors except the rating that influence the credit terms, some of which are cross-selling, competition and similar aspects. We return to this point later because these variables are explicitly incorporated in the regression. Second, the results may be due to the fact that the analysis only contains credits on current account for the entire sample period 1992-1996. Provided the bank does not terminate the lending relationship with the firm, those credits are usually extended on a year-by-year basis. If the terms of these credits are not continuously adjusted for possible changes of the respective firm´s rating over time, the detection of significant relationships between the rating and the *IRP* would be hampered. But even if this last interpretation should be true the question of why banks behave that way remains still to be answered. Since we are currently not able to answer that question we must leave it for future research.

With respect to the other firm variables, our regression illustrates a negative relationship between the equity ratio ER and the interest rate in sample A. This predicted result is statistically significant at the 10 percent probability level. For sample B, the respective coefficient is insignificant and has the „wrong“ sign. The return on total assets RT is generally insignificant and in the „wrong“ direction, while the size measure LNSALES is significant (at different levels) in both samples[19].

[19] This is consistent with the findings of *Blackwell/Winters* (1997).

2.2.2 Credit variables

In both samples the coefficients for the collateral variable UNCOL are negative and significant at least at the 5%-level. The coefficient for COV is positive in both samples but only significant in sample A at the 5%-level. These results are not consistent with the combined agency- and signaling arguments outlined in section 2.1.2 above. According to this theory we should observe higher interest rate premiums for firms with lower collateral and less covenants contradicting the results in table 2. On the other hand, if the converse signaling-hypothesis holds then „good“ firms are not required to pledge much collateral and to install covenants, and they should receive better credit terms, a view that is confirmed by our regression. With respect to the pure contracting theory the empirical results are consistent as far as it is hypothesized that the riskier firms find it more profitable to use collateral and to install covenants, and that this effect cross-sectionally dominates the individual interest-reducing effect of using such mechanisms. As was already mentioned above, however, the premium-regression alone does not allow for a final judgment regarding the three competing hypotheses. The Logit-results of section 3 have also to be taken into account.

Regarding the variables for cross-selling CS and competition HHI, both variables are significant in sample A while only HHI is significant in sample B. However, comparing the sign of the coefficients for both samples is somewhat puzzling. The cross-selling variable works in the expected direction only in sample A but not in sample B, while the competition index HHI (generally significant at the 1%-level) has the expected sign only in sample B. In explaining these findings one could argue that the CS-values can be attributed to the characteristics of the two samples. In particular, the firms in sample B are firms that the banks have marked as „firms with *potential* problems“[20]. Provided that the prospects of future transactions other than lending are lower for sample B-firms, cross-selling arguments should indeed play no role for those firms which is consistent with the findings in table 2.

More difficult is, however, the explanation for the HHI-results. Extending the line of reasoning for the CS-variable to the HHI-index one could argue that firms with potential problems find it more difficult to obtain credit from other banks. Hence, an incumbent bank can possibly better use its monopoly power in a certain region for sample B-firms. But this

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[20] See for a more detailed description of the samples *Elsas et al.* (1997).

does not explain why the HHI-coefficient is *negative* in sample A. We suspect that this is at least partly due to the construction of the HHI-index wherein regions according to zip-codes play a great role. If competition would be more broadly defined (e.g., one could argue that in the age of computer and communication the entire world is the „relevant" market for financial transactions), the HHI-index is a too narrow measure of competition. Thus, the findings with regard to the HHI-index should be interpreted with caution and just be viewed as a first step.

Finally, in both samples all variables that can somehow be linked with housebank-relationships (HB, NUM, BCP) are insignificant (although most of them have the predicted sign). This is in contrast to the findings of other studies[21] where relationship variables often proved to be significant explanatory variables. A direct comparison is, however, difficult due to completely different data sets and varying variables.

2.2.3 Additional control variables and refinements

Relative to the manufacturing sector only firms of the service sector (other sectors) in sample A (sample B) have significantly different interest rate premiums. The remaining industry variables are not significant.

As can be seen in table 2 all year dummies are highly significant and strictly increasing in time for both samples. This suggests that separate regressions for each year could possibly yield additional insights into potential year-specific structures. However, running the regressions for each year separately gives the following results of table 3 (The table only includes sample A because sample B contains not enough cases for a meaningful subdivision. The levels of significance are marked as in table 2):

[21] *Petersen/Rajan* (1994), *Berger/Udell* (1995), *Blackwell/Winters* (1997)

Variables	**1992 (N=59)**	**1993 (N=58)**	**1994 (N=56)**	**1995 (N=64)**	**1996 (N=62)**
Intercept	4.2402**	5.5102*	8.1398*	8.2052*	7.3523*
Firm variables					
RAT3 (+)	.0896	.4164	.3533	.3037	.3765
RAT4 (+)	-.0176	.7341	.5003	.3766	-.087
RAT5 (+)	#	.0156	.6896	.7745	.7278
ER (-)	.0003	.0013	-.0094	.0015	-.0098
RT (-)	.0001	.0063	.0081	.0011	.0011
LNSALES (-)	-.1727	-.1748***	-.3855**	-.2501	-.175
Credit variables					
UNCOL (?)	-.0029	-.0053	-.0059	-.008**	-.0055
COV (?)	.4521	-.1241	-.2319	.6453**	.3739
CS (-)	-.3055	-.2998	.4263	-.3108	-.3452
HHI (+)	-.824	-1.1053	.6276	-1.8548	-3.7395***
HB (-)	-.2073	.1588	.0327	-.2752	-.0968
NUM (+)	.0027	-.0182	.0055	-.0358***	-.0183
BCP (?)	-.2025	-1.0639	-.5199	-1.4922	-1.0524
Bank dummies					
Bank 2	.2375	.3033	-.1787	-.4969	-.1915
Bank 3	.4802	.6307	.3093	.1104	.3027
Bank 4	.1589	.3523	.1029	-.4214	.0267
Bank 5	.0543	.6107	.1703	-.135	.2085
Industry dummies					
Construction	-.0251	-.0712	.4258	.1184	.6179
Service	.4204	.3732	-.5407	-.1834	.3838
Trade	.023	-.1169	-.2511	-.2185	.4801
Other	-.2435	-.2393	.4135	-.1306	-.1906
Adjusted R^2	-.1773	.1035	.2749	.3608	-.0587
F-statistics	.5633	1.3134	1.9927***	2.6932*	.8389

Table 3: OLS-regression results for *IRP* differentiated by year, Sample A

*	Significant at the 1%-level
**	Significant at the 5%-level
***	Significant at the 10%-level
#	No case with this characteristic found

In view of table 3 it seems difficult to detect any systematic relationships for the single years. The regressions generally have relatively low explanatory power. According to the F-statistic only the regressions for 1994 and 1995 are significant at all, and within each year just a few variables (if any) are individually significant. This may partly be due to the low number of cases for each year compared to the number of variables, an indicator of which is the *negative* adjusted R^2 that is obtained for the two years 1992 and 1996.[22] In any case, taking a more diffentiated view at the data by dividing the sample on a year-by-year basis lets the results appear extremely heterogeneous. Only a few variables have a consistent sign during all years. In the year with a relatively acceptable explanatory power (1995), the two collateral variables UNCOL and COV are both significant and have the same signs as in table 2. Furthermore, 1995 is the only year in which one of the relationship-banking variables (NUM) gets significant, but unfortunately it has the „wrong“ sign.

With regard to the bank dummies table 2 reveals that there is indeed one bank (bank 3) that is obviously able to consistently charge higher interest rate premiums than all other banks in both sample groups. This raises the question of whether the parameters chosen for our analysis affect the credit policy of different banks differently. In order to answer this question we subdivided the credit sample by the five banks and run the regression separately for each bank. The results are summarized in table 4 (The statistical significance is again marked in accordance with table 2. For the same reasons as in table 3 the results of table 4 only cover the cases of sample A. Furthermore, the numbering of the five banks has been changed relative to tables 2 and 3 to keep the banks from being detected):

[22] This argument, however, is a very tentative one and cannot fully capture the variability of the statistical results in table 3. For instance, subdividing the data by banks (which will be done in the text immediately) and analoguously performing separate regressions with essentially the same number of variables yields results of a very good explanatory power according to the usual measures.

Variables	**Bank 1 (N=66)**	**Bank 2 (N=68)**	**Bank 3 (N=44)**	**Bank 4 (N=81)**	**Bank 5 (N=40)**
Intercept	4.454*	.0353	3.4465	7.6516*	5.1837***
Firm variables					
RAT3 (+)	.0976	-.1103	1.3717	.1055	-.1075
RAT4 (+)	-.01125	.0602	.9128	.0268	-.9208
RAT5 (+)	-1.2365**	.0689	#	.1378	-.5646
ER (-)	-.0147*	.0168	.0023	-.0192**	.0203
RT (-)	.0052	-.0013	-.0126	-.0025	-.0028
LNSALES (-)	-.0583	.2001	-.1879	-.3911**	-.1373
Credit variables					
UNCOL (?)	-.0052	-.0103**	-.004	-.0027	-.0052
COV (?)	.5156**	-.266	-.3351	.4537**	.4147
CS (-)	-.041	.4325	.013	-.3469	-.5518
HHI (+)	-.6394	-2.9723***	-.2632	-5.694**	-4.6724
HB (-)	-.6609*	1.6887*	-.0122	-.3941***	-.4485
NUM (+)	-.0447	-.0567***	-.0191	-.0102	-.0849
BCP (?)	-.6149**	2.8226***	-.7284	2.0508**	-2.2498
Industry dummies					
Construction	.2805	.5618	.7672	.8606***	#
Service	.0286	2.9549*	#	-.585	#
Trade	-.5377**	1.3437*	1.8894	.1531	-.4358
Other	-.2513	-1.5868*	.3299	.8197**	-1.4784
Year dummies					
1993	1.0883*	1.3603*	1.4409**	1.5619*	1.5625*
1994	1.5108*	1.7154*	1.9858*	1.7773*	1.8317*
1995	1.2945*	1.4732*	1.993*	2.0071*	2.1048*
1996	1.6065*	1.8799*	1.641*5	2.2424*	2.2392*
Adjusted R^2	.7174	.6462	.4039	.6808	.6886
F-statistics	8.8558*	6.8269*	2.5337**	9.1246*	5.5398*

Table 4: OLS-regression results for *IRP* differentiated by banks, Sample A

*	Significant at the 1%-level
**	Significant at the 5%-level
***	Significant at the 10%-level
#	No case with this characteristic found

The results of table 4 confirm statements in the literature[23] that the lending business seems to be governed by highly idiosyncratic elements. The set of significant variables and their respective coefficents differ considerably between the five banks except for the year-dummies: They consistently have positive signs. Furthermore there is some common factor with regard to the rating-dummies in that *almost all rating variables are insignificant* except RAT5 of bank 1, but its coefficient has the „wrong“ sign. Moreover, such unpredicted signs appear relatively often within the rating dummies (in more than 40% of the respective coefficients).

The high extent of idiosyncrasy can best be seen by looking at some remarkable aspects. Compare, e.g., bank 2 and bank 4 with respect to the following selected firm- and credit-variables (the selection criteria are different signs or/and different significance in the sense that a certain variable is significant for one bank but not for the other bank):

Selected firm- and credit- variables	**Bank 2**	**Bank 4**
ER (-)	.0168	-.0192**
LNSALES (-)	.2001	-.3911**
UNCOL (?)	-.0103**	-.0027
COV (?)	-.266	.4537**
CS (-)	.4325	-.3469
HB (-)	1.6887*	-.3941***
NUM (+)	-.0567***	-.0102

Table 5: Selected variables for bank 2 and bank 4

Table 5 shows that many variables seem to work in opposite directions in the two banks. Especially remarkable is the coefficient for the relationship dummy HB, which is significantly positive (negative) for bank 2 (bank 4). This implies that firms having a house bank relationship with bank 2 are charged not only higher interest rate premiums than in bank 4, but they are also charged higher interest rate premiums (*ceteris paribus*) than without a house bank relationship at bank 2. Thus, the question arises as to why firms would find it profitable to enter into a house bank relationship with bank 2 at all, because it is hardly imaginable that firms do not realize these structures of credit terms over time. We suggest that there must be other (qualitative) factors in lending relationships that are not

[23] See, e.g., *Berger/Udell* (1995), p. 367.

fully captured by existing approaches. These factors finally translate into quantitative terms because they obviously allow certain banks to charge higher interest rate premiums which may constitute a basis for earning abnormal returns without having to suffer from competitive pressures. The specific nature of these factors and their resistance against competition remains up to now an open question that may be tackled by future research.

2.2.4 Summary of the results for the surplus -question

Summarizing the results for the premium-regressions we state that the findings differ according to the perspective that the data are viewed with. Taking a global view on the data some structures emerge for the individual samples according to table 2. If, however, a more specific point of view is taken by subdividing the data by year or by banks, the picture changes. The structures that seem to emerge from the global view do not carry over to the individual years and/or the individual banks. But at least some regularities can be identified. First, the rating of the banks is largely insignificant. Secondly, the year-dummies are consistently significant in the global regression and in the individual bank analyses. Finally, regarding the credit factors the collateral variable UNCOL has a consistently negative sign in all global and individual regressions (although the coefficient is not always significant).

3. Determinants of distress-probabilities

3.1. Procedure and variables

In order to get some insights into the determinants of the frequency of potential „disturbances“ we performed a Logit analysis. Our aim was to investigate, whether there is any systematic relationship between factors available at the beginning of the sample period (1992) and the occurence of problems hereafter. For that purpose we first classified the entire sample of credit *engagements* (200 firms) into „distress-cases“ and „non-distress-cases“[24]. A credit engagement is called „distressed“ if - during the period 1993-1996 - at least one of the following events occured:

- Initiation of formal insolvency proceedings,
- utilization of collateral by the bank,
- valuation adjustments of the bank´s claims,
- initiation or planning of restructuring activities by the bank and/or
- termination of the bank´s engagement.

These criteria comprise a broad spectrum of potential problems that may occur during a credit engagement. Each criterion involves specific costs that lower the bank´s return from lending to the respective firm. Note that the classification procedure does not rely on the firm rating nor is it applied to the sample group „B“ only. Thus, „distress-cases“ as defined here can basically occur even for a firm with the best 1992-rating in sample group „A“. Applying these criteria to the entire sample we first obtained 47 distress-cases (coded „1“ for Logit purposes) and 153 non-distress-engagements (coded „0“). After excluding those cases that were already distressed in 1992 a total of 31 distress-cases remained.

We then regressed this dependent Logit-variable on several factors from the year 1992. By this means it can be seen whether data from the beginning of our sample period is systematically related to the frequency of later „disturbances“ as defined above. Additionally the results of the analysis may also serve as a kind of „distress-prediction“ model analogous to numerous models for bankruptcy prediction that are based on either Multivariate

[24] The analysis in this chapter concentrates on the complete credit engagement (i.e., the firm that is granted credit by a bank) instead of looking at single credits. The reason is that potential „disturbances“ can hardly be traced to any single credit but are regularly caused by the firm´s total debt and the investment program.

Discriminant Analysis[25] or Logit approaches[26]. We will return to this second point after presenting our Logit results.

The set of independent variables from 1992 is principally based on the set of variables for the premium-regressions in chapter 2 with some modifications. With respect to the *firm variables*, we first include the rating as described in chapter 2 as a compound measure of various aspects that are relevant for the firm´s risk-return-characteristics as evaluated by the respective bank. Additionally we incorporate three financial ratios that are usually employed in financial statement analyses as important measures for long-term financial risk. These are the equity-ratio ER (already used in chapter 2), the cash-flow-ratio CF defined as „cashflow/total debt“[27] and the coverage ratio for long term assets CLTA, which is given by „(equity + long-term debt)/(long-term assets)“. For all three variables the same qualitative hypothesis holds: The higher the respective ratio the lower the distress probability should be. Finally to control for firm size LNSALES is included again.

With respect to the *credit engagement variables* we first incorporate UNCOL (the percentage of the bank´s claims that are uncollateralized) and COV (the dummy variable for the existence of covenants). As was already the case in chapter 2 the hypotheses regarding the sign of the coefficients for these two variables depend on the respective theory. According to combined agency- and signaling-arguments we should observe a negative relationship between the amount of collateral and/or covenants and the distress probability, which amounts to a positive (negative) sign for UNCOL (COV). Conversely, if the reverse-signaling arguments are employed, the sign for UNCOL (COV) should be negative (positive). Again, no clear-cut statement is possible for the pure contracting theory.

Regarding the *credit engagement variables* we further include the number of banks NUM and the relationship lending variable HB. For reasons already explained in chapter 2 the hypothesized effect for the distress probability is positive for NUM and negative for HB. Consistent with our assumption that total indebtedness is responsible for potential problems we do not include the variable BCP. Moreover the bank competition measure HHI is not used in the Logit model because we cannot see any reason why the competition between

[25] See, for example, *Altman* (1968), *Gebhardt* (1980), *Zavgren* (1983) and *Baetge/Huss/Niehaus* (1988).
[26] See, e.g., *Ohlson* (1980) and *Anders* (1997). A comparison of the models of *Altman* (1968) and *Ohlson* (1980) with more recent data is contained in *Begley/Ming/Watts* (1996).
[27] This is the reciprocal value of the so-called „dynamic leverage ratio“ which describes the number of years that are needed to repay the total debt obligations by using the firm´s cash flows.

banks (which may be important at the time the funds are raised by the firm) should have any systematic relationship to the probability of *later* problems mentioned at the beginning of this chapter.

To control for possible industry effects we include the industry dummies as described in chapter 2. Dummys for individual years are not needed since our Logit analysis captures the occurrence of problems during an entire period (1993-1996). Bank dummies are also not incorporated; our selection procedure for the distress-cases (i.e., exclusion of all engagements that were already distressed in 1992) combined with the limited number of observations affects the five banks differently. Thus, including bank dummies would probably bias the results.

Because we couldn´t obtain 1992-ratings for all engagements, the sample had to be reduced further. It finally consisted of 30 distress-engagements and 122 non-distress-engagements[28].

3.2. Description of the data

In order to get a first impression of the structure of the 1992 data, the following table depicts the mean values for the independent variables differentiated for distress- and non-distress-cases:

	Distress-engagements	**Non-distress-engagements**
RAT	3,8333*	2,9672*
ER	0,1662**	0,2309**
CF	0,2877*	0,5893*
CLTA	0,9016	1,1492
LNSALES	11,3602	11,6625
UNCOL	0,7415	0,7031
COV	0,0323	0,093
NUM	7,2745	5,9047
HB	0,2258	0,3798

Table 6: Mean values 1992, Logit Analysis

(*: Difference significant at the 1%-level)
(**: Difference significant at the 5%-level)

[28] To alleviate problems of data availability with respect to the other 1992-variables, we substituted missing values with the sample-mean values for the respective variable.

As can be seen from table 6 the relation between the means is in the expected direction for most variables (of course, with respect to UNCOL and COV the „expected" direction depends on the theory chosen), although significant deviations are obtained only for RAT, ER and CF. With respect to the rating it may be interesting to look at the rating distributions for the two groups of engagements:

Figure 1: Rating distribution 1992, non-distress-cases

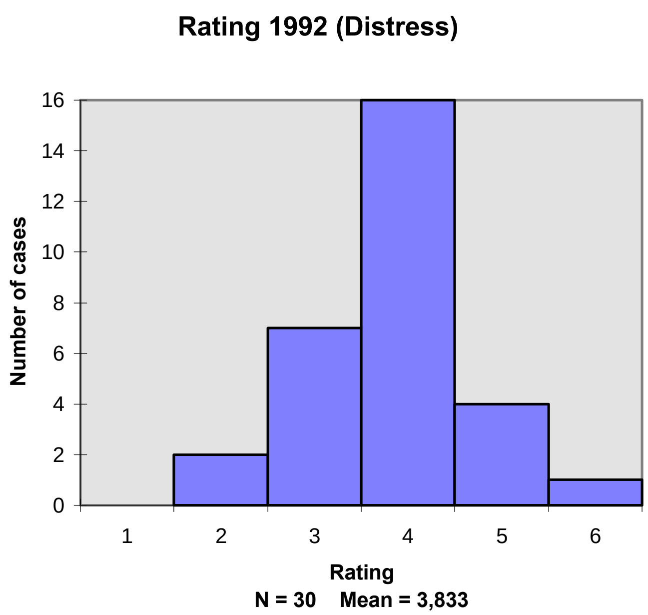

Figure 2, Rating distribution 1992, distress-cases

The two figures show clearly the differences between the two groups. In the non-distress-group the most cases are rated 3 while in the distress-group they are rated 4. Furthermore there are no engagements with rating 1 that become distress during the following years, and the one firm with rating 6 does not switch to the non-distress-group. On the other hand there are good rated firms that become distressed as well as below-average-rated firms that do not encounter any problems during the period 1993-1996.

3.3. Logit-results

For the Logit regression we further excluded the one extreme „rating 6“ case from the analysis. The following table contains the Logit-results[29]:

Variable	**Coefficient**
ER	-0,143
CF	-0,5418
CLTA	-0,0092
RAT-3	0,2228
RAT-4	1,2051
RAT-5	2,0143***
LNSALES	-0,9473*
UNCOL	0,0189***
COV	-2,0181
NUM	0,068
HB	-0,7956
Constant	8,7848
McFadden R^2 = 0,281 Model χ^2 = 41,406* (Degrees of freedom: 18) *: Significant at the 1%-level ***: Significant at the 10%-level	

Table 7: Logit-results

The summary statistics for the model reveal that it explains a considerable part of the relationship between the dependent and independent variables. Although the entire model is

[29] The results for the industry dummies are not reported because of their large insignificance.

highly significant there are only three coefficients that are individually significant. As in the premium-regressions of chapter 2 the firm size variable LNSALES has again a significant influence: The probability of distress decreases with a greater firm size. Furthermore, the collateral variable UNCOL is significantly related to the probability of distress in that a higher percentage of uncollateralized credits leads to a higher incidence of problems in the following years. Stated differently *more collateral seems to be connected to a decrease in the distress probability*, an interpretation that is confirmed by looking at the coefficient for the covenants dummy COV which is negative (and only marginally insignificant).

Thus, the Logit results for the monitoring and bonding variables contradict the „reverse signaling hypothesis". According to this hypothesis riskier firms are required to pledge collateral and to install monitoring and bonding mechanisms, which should result in a negative sign for UNCOL and a positive sign for COV. Conversely the Logit results support the combined agency- and signaling theory, according to which better firms can signal their true quality by offering more and/or tighter collateral and covenants respectively. However, looking back at the results of the premium regressions, if the combined agency- and signaling hypothesis holds we should observe a negative relationship between the *IRP* and the use of collateral and/or covenants. Since this is not supported by the premium regressions, the empirical results of both regressions do not completely corroborate the combined agency- and signaling theory.

One possible interpretation of the sign of UNCOL and COV is that the monitoring and bonding devices are really useful in reducing debt-related agency problems. Therefore, the incidence of potential „disturbances" should decrease the more colletaral and/or covenants are used, and this is confirmed by the empirical results. At first glance this argument is consistent with the pure contracting theory - but only because the predictions of that theory are somewhat indetermined regarding the sign of the coefficients in a cross-section. A corroboration of the above line of argument could be obtained if the premium regressions of chapter 2 revealed negative relationships between UNCOL and/or COV and the *IRP*, but this is not the case. Thus, if all empirical results of this paper are taken together, we get interpretations that are partially consistent and inconsistent with either of the three hypotheses, and at the current time one cannot give any clear-cut statement.

With respect to the rating variable all dummies are in the hypothesized direction (higher ratings yield higher probabilities of distress) but only the dummy for the worst rating 5 is significant. Hence a similar conclusion as in the premium-regressions emerges: The banks´ rating is - given all other variables of the above multivariate analysis - somewhat surprisingly not as significant as one would normally expect, although it incorporates various qualitative and quantitative sources of information about firms.

All other coefficients have the predicted sign, but they are individually insignificant. Higher values for the three debt-related firm variables (ER, CF, CLTA) show a negative relationship with the distress probability. The higher the number of lenders the higher the probability of distress, and a relationship lending contract seems to be related to a lower distress probability.

3.4. Distress prediction

Inserting the 1992 data for an individual firm into the Logit equation yields a firm-specific probability of distress. The mean values for the distress-group (non-distress-group) are 0,4273 (0,1373), and the differences are significant at the 1% level. This suggests that the Logit results are able to „separate“ the two groups of engagements. The data for the entire sample result in a distribution of distress probabilities. Analogous to *Ohlson* (1980) one can use this distribution to compute a „cutoff“-probability $\hat{p}$ such that all firms with individual probabilities higher (lower) than $\hat{p}$ are classified as distress (non-distress). This information can in turn be used by a bank in the credit decision process. Note that the individual rating of the bank is only part of the information that is contained in the individual distress probabilities. Furthermore, even though the procedure is analogous to the one employed in traditional bankruptcy prediction models, there are differences to our analysis in so far as the case of insolvency is just one criterion for „disturbances“ in our study.

The difficulty in determining the cutoff $\hat{p}$ results from the different types of errors that a classification may produce. A type I (II) error occurs if a really distressed (non-distressed) firm is classified as non-distressed (distressed). The „optimal“ cutoff essentially depends on the relative magnitudes of the costs of both errors. For instance, if the cost of a type I error is much larger than the cost of a type II error, the cutoff $\hat{p}$ should take on relatively low values because then more firms are classified as distress-firms. The concrete empirical magnitudes of the costs of both errors are not known, but in the context of bankruptcy prediction models it is usually assumed that the costs of a type I error are considerably greater than the costs of a type II error[30].

In order to get some impressions about the sensitivity of the cutoff $\hat{p}$, we employed a parametric procedure similar to the one used by *Dopuch/Holthausen/Leftwich* (1987) in a methodological related but otherwise totally different context (prediction of audit qualifications). According to this procedure the cutoff $\hat{p}$ is computed by minimizing the expected *ex ante*-misclassification costs $EC(\hat{p})$, which are defined as follows:

$$EC(\hat{p}) = p_d \cdot f(d|\hat{p}) \cdot C_I + (1 - p_d) \cdot f(n|\hat{p}) \cdot C_{II} \tag{1}$$

Herein are:

p_d:	a-priori-probability of distress
$f(d\|\hat{p})$:	conditional probability of a type I error (i.e., a distress firm is classified as non-distress) given $\hat{p}$
$f(n\|\hat{p})$:	conditional probability of a type II error (i.e., a non-distress firm is classified as distress) given $\hat{p}$
C_I:	Cost of a type I error
C_{II}:	Cost of a type II error

The conditional probabilities $f(d|\hat{p})$ and $f(n|\hat{p})$ are determined from the Logit sample, while the error costs and the a-priori-probability p_d are still unknown. However, to get insights into the sensitivity of the cutoff values it is sufficient to parametrically vary the costs and the a-priori-probability. For that purpose we express the costs of a type I error in the following way:

$$C_I = a \cdot C_{II} \tag{2}$$

Inserting equality (2) in expression (1) shows that only the parameter a influences the results of the optimization procedure given p_d. Since the type I error costs are assumed to be larger than the costs for type II errors, we run the optimization alternatively for a-values of 1 to 20. Regarding the a-priori-probability p_d we orientate ourselves on statements of practitioners according to which that probability should be considered as small. Thus, we

[30] See e.g. *Begley/Ming/Watts* (1996).

run the optimiziations for p_d-values of 2%, 3%, 4% and 5%. The following table summarizes the results:

α	$p_d = 0{,}02$	$p_d = 0{,}03$	$p_d = 0{,}04$	$p_d = 0{,}05$
1	0,57305	0,57305	0,57305	0,57305
5	⋮	⋮	⋮	0,48744
6	⋮	⋮	0,48744	⋮
8	⋮	0,48744	⋮	⋮
12	0,48744	⋮	⋮	
14	⋮	⋮		0,40376
18	⋮	⋮	0,40376	0,14379

Table 8: Optimal cutoff probabilities $\hat{p}$

The table contains only those a-values for which a change in the cutoff $\hat{p}$ occurred. The results reveal that the cost-minimizing cutoff remains relatively stable for low values of p_d but shows considerable variation for $p_d = 0{,}05$. The total percentage of misclassified firms ranges from 12,5% ($\hat{p}$ = 0,57305) up to 29,6% ($\hat{p}$ = 0,14379). But these percentages are not very meaningful if viewed in isolation because they do not contain any information about the misclassification costs. For instance, the percentage 29,6% for the cutoff $\hat{p}$ = 0,14379 may seem relatively high, but no other value can do better if the a-priori-probability of distress equals 0,05.

Our results suggest that for classification purposes it may be very important to specifiy the a-priori-probabilities of distress and the cost relations for the two error types. We would like to mention that these aspects are usually not dealt with in prevailing bankruptcy prediction models. Yet our results are of a preliminary nature in so far as we do not have enough data to form a control group against which the performance of the Logit model could be tested. For such control purposes it would also be interesting to compare the Logit model to alternative approaches, e.g., neural networks[31]. We hope to be able to report about such investigations in a later paper.

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[31] Due to several statistical problems and the results of the comparison in *Begley/Ming/Watts* (1996), prediction models using multivariate discriminant analysis seem to be inferior to Logit approaches. See for first comparisons of logit models versus neural networks *Anders* (1997).

4. Summary

The possibilities to empirically identify structural relationships regarding the determinants of bank lending performance obviously depend on the level of aggregation. The more differentiated the analysis is performed the more heterogeneity emerges from the data (e.g., the same factors seem to work differently for different banks). Only factors related to collateralization and the existence of covenants seem to be of a relatively basic importance. However, explaining the results with respect to these two factors is a „puzzle“: On the one hand, more collateral seems to be related to higher interest rate premiums. On the other hand, more collateral is linked with lower distress-probabilities. Stated differently, the *results seem to suggest that credit contracts are priced lower where the risks are greater*! An explanation for that finding is still missing, and this could be a starting point for further theoretical and empirical analyses. In addition we have indicated in the text several problems that should be addressed by future research, e.g., the measurement of the degree of competition and the question of why there seem to be „walls against competition“ that allow at least some banks to consistently earn relatively high interest rate premiums.

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