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The importance of qualitative risk assessment in banking supervision before and during the crisis

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Abstract

Banking supervision requires regular inspection and assessment of financial institutions. In Germany this task is carried out by the central bank (*"Deutsche Bundesbank, BBK"*) in cooperation with the Federal Financial Supervisory Authority (*"Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin"*). In accordance with the Basel II approach, quantitative and qualitative information is used. It is still an open question whether supervisors provide information, based on on-site inspections, which is not known from the numbers already, or simply duplicate the quantitative information, or even overrule it by their impressions gained through visits. In our analysis we use a unique dataset on financial institutions' risk profiles, i.e. the banking supervisors' risk assessment. Methodologically, we apply a partial proportional odds model to explain the supervisor's ordinal grading by a purely quantitative CAMEL covariate vector, which is standard in many bank rating models, and we also include the bank inspector's qualitative risk assessment into the model. We find that not only the quantitative CAMEL vector is clearly important for the final supervisory risk assessment; it is, indeed, also qualitative information on a bank's internal governance, ICAAP, interest rate risk, and other qualitative risk components that plays an equally important role. Moreover, we find evidence that supervisors have become more conservative in their final judgement at the beginning of the financial crisis, i.e. the supervisory assessment seems to be more forward-looking than the mere numbers. This result underpins the importance of bank-individual on-site risk assessments.

Key words: bank rating, banking supervision, generalized ordered logit

JEL: C35, G21, G32, L50

Non-technical summary

The current financial crisis has highlighted the importance of the banking industry for the real economy. Hence, the banking system is subject to stricter and more intensive supervision than most of the other industries. In Germany the ongoing monitoring of credit and financial services institutions by the central bank (*"Deutsche Bundesbank, BBK"*), in cooperation with the Federal Financial Supervisory Authority (*"Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin"*), ensures the stability of individual banks as well as the stability of the financial system as a whole.

In this paper we introduce a model of the supervisory risk assessment. We use a unique database on the institutions' supervisory risk profiles for the years 2006 through 2008. The risk profile of a bank comprises an evaluation of its overall risks, its organization and internal control procedures, and its risk-bearing capacity. The risk profile is divided into partial grades of twelve quantitative and qualitative criteria. The aim of this paper is to make three contributions towards the further development of supervisory bank rating models.

The first is to explain the supervisory assessment of a bank's risk profile, in contrast to distress or default events used in previous studies, in the model. As supervisory risk profiles are divided into four categories, A, B, C, and D, where A is the best and D the worst grading, we use an ordinal estimation technique. More precisely, we specify a partial proportional odds model (PPOM) which, owing to theoretical considerations and practical properties, is best practice in this kind of analysis.

The second is to include ("soft") qualitative factors in the regression model in addition to a purely quantitative CAMEL covariate vector which is frequently used in bank rating models. The qualitative factors are taken from the supervisor's partial grading of an institution's internal governance, internal capital adequacy assessment process (ICAAP), interest rate risk, and other qualitative risk components. We find that qualitative factors are highly significant in the PPOM regression statistics, i.e. in comparison to the purely quantitative CAMEL vector they play an equally important role in explaining the supervisor's final assessment of an institution. Moreover, we find evidence that supervisors have become more conservative in their final judgement at the beginning of the crisis, that is the risk assessment by the supervisor seems to be more forward-looking than the mere numbers. A reasonable categorization and the forward-looking character of the risk profiles is also confirmed by validation with additional distress information that is available at the Deutsche Bundesbank. This result underpins the importance of bank-individual on-site risk assessment as a complement to off-site quantitative analysis in order to obtain a comprehensive picture of a bank's risk profile.

The third contribution of the paper is to introduce a rating tool for banking supervision to ensure equal standards in the assessment of individual banks. The rating tool gives information on how an “average” supervisor would rate a given bank taking into account quantitative factors (taken from supervisory accounting data) and qualitative factors (taken from partial grading). We find that the PPOM assigns roughly two thirds of the banks to exactly the same rating class as the supervisor, and more than 99% to the same or to a neighboring rating class.

Nichttechnische Zusammenfassung

Die derzeitige Finanzkrise hat die überragende Bedeutung des Bankensektors für die gesamte Volkswirtschaft noch einmal klar gezeigt. Gerade aufgrund seiner Wichtigkeit unterliegt deshalb das Bankensystem einer strikteren und intensiveren Aufsicht als die meisten anderen Wirtschaftsbereiche. In Deutschland wird die laufende Überwachung der Kredit- und Finanzdienstleistungsinstitute durch die Deutsche Bundesbank, in Zusammenarbeit mit der BaFin, durchgeführt. Ziel dieser Aufsicht ist es, sowohl die Stabilität einzelner Banken als auch die des gesamten Finanzsystems sicherzustellen.

Im vorliegenden Papier wird ein Modell zur Erklärung der bankenaufsichtlichen Risikobewertung vorgestellt. Datenbasis ist dabei die Risikoprofileinschätzung der Institute durch die Bankenaufsicht für die Jahre 2006 bis 2008. Das Risikoprofil einer Bank umfasst die Bewertung aller Risiken des Instituts, seiner Organisation und internen Kontrollverfahren sowie seiner Risikotragfähigkeit, welches sich aus einer Gesamtnote sowie Teilnoten bezüglich zwölf quantitativer und qualitativer Kriterien zusammensetzt. Primäres Ziel der Untersuchung ist es, einen Beitrag zur Weiterentwicklung von bankenaufsichtlichen Ratingmodellen zu leisten. Zentrale Aspekte sind hierbei wie folgt:

Erstens wird die bankenaufsichtliche Risikoeinschätzung (statt wie in bisherigen Studien Bankenausfälle oder Problemereignisse bei Banken) als abhängige Variable im Modell erklärt. Aufgrund der Skalierung des Risikoprofils in die Kategorien A, B, C und D, wobei D Probleminstitute kennzeichnet, wird ein Schätzverfahren für eine ordinale abhängige Variable herangezogen. Konkret wird ein sog. “Partial Proportional Odds”-Modell (PPOM) spezifiziert, welches aufgrund theoretischer Überlegungen und praktischer Eigenschaften als “best practice” für diese Art der Analyse anzusehen ist.

Zweitens werden in das Modell (“weiche”) qualitative erklärende Faktoren mit einbezogen, welche den in vielen Bankenratingmodellen verwendeten rein quantitativen CAMEL-Vektor ergänzen. Die qualitativen Faktoren entstammen dabei den bankenaufsichtlichen Teil-Risikoeinschätzungen zur internen Organisation des Geschäftsbetriebs, zum Internal Capital Adequacy Assessment Process (ICAAP), zu Zinsrisiken sowie zu sonstigen qualitativen Risiken der Institute. Die Regressionsergebnisse zeigen einen hoch signifikanten Einfluss dieser qualitativen Faktoren auf die bankenaufsichtliche Bewertung eines Finanzinstituts, wobei sie im Ratingmodell in etwa die gleiche Bedeutung wie der rein quantitative CAMEL-Vektor haben. Darüber hinaus finden wir in unserer Analyse Hinweise darauf, dass die bankenaufsichtliche Risikoeinschätzung im Jahr 2008 konservativer geworden ist und damit die Bankenaufseher die Krise schneller antizipieren konnten, als dies durch die rein quantitativen Kennzahlen möglich war. Die “Qualität” sowie der zukunftsgerichtete Charakter der Risikoprofileinschätzung wird durch die Validierung mit weiteren Distress-Indikatoren bestätigt. Dieses Ergebnis verdeutlicht die

Notwendigkeit einer bankindividuellen Risikoeinschätzung zur Ergänzung rein quantitativer (bspw. auf Bilanzdaten basierter) Analysen, um hierdurch ein wirklich umfassendes Bild über das Risikoprofil eines Instituts zu erhalten.

Der dritte Beitrag dieses Papiers ist die Spezifikation eines Ratingmodells zur Qualitätssicherung bei der bankenaufsichtlichen Einschätzung von Instituten. Das Ratingmodell zeigt auf, wie ein "durchschnittlicher" Bankenaufseher ein Institut unter Berücksichtigung quantitativer Faktoren (entnommen aus Bankjahresabschlüssen) sowie qualitativer Faktoren (entnommen aus den bankenaufsichtlichen Teil-Risikoeinschätzungen) einordnet. Dabei zeigen wir, dass das PPOM etwa zwei Drittel der Banken in exakt die gleiche bzw. mehr als 99 % in die gleiche oder in eine benachbarte Kategorie wie der Bankenaufseher einstuft.

Contents

1. Introduction

The current financial crisis has again emphasized the importance of monitoring and analyzing financial institutions. In the last few years, rating models have gained increasing importance at central banks in identifying vulnerabilities at individual institutions as well as for assessing the stability of the financial system as a whole. Improving the available bank rating techniques and enhancing their scope contributes to a more efficient evaluation of financial institutions and provides important information for banking supervisors.

There are numerous early studies on predicting bank defaults with financial data for the US banking sector, such as Sinkey (1975), Martin (1977), and Altman (1977). While discriminant analysis was the preferred method up to the mid 1980s, later on maximum-likelihood estimators (cf. the early work of Martin) became the standard methodology in bank rating because of their statistical properties. Logit and probit specifications are particularly favorable as they directly estimate PDs; see also Porath (2006) for a detailed overview of the bank rating literature. Moreover, in 1987 the National Credit Union Administration (NCUA) adopted the so called CAMEL rating system to measure risk in the areas of Capital Adequacy, Asset Quality, Management, Earnings, and Liquidity; purpose of the rating system is to allocate resources for supervision (NCUA, 1994).

The definition of default and distress is crucial for any bank rating study. Outright bank defaults, however, are rare and the narrow definition of observed and ultimate bank defaults is mostly not adequate for such rating models. Hence, most US studies define default either as closure by regulators due to capital ratios falling below two percent or a merger assisted by the Federal Deposit Insurance Corporation (Cole and Gunther, 1995). For the German banking system in the last few years there have been several studies on bank distress and bank default which are based on a unique dataset of distress and default events collected at the Deutsche Bundesbank. In the early stage Porath (2006) applied hazard models to transform a set of bank-specific and macroeconomic covariates into the probability of default (PD) using appropriate link functions such as logit, probit, and the complementary log-logistic (cloglog) function. The specification of an adequate lag between covariates and default events ensures that the individual bank PD in a given year, PD_{it}, is the probability that this bank defaults within one year.

In a subsequent study Kick and Koetter (2007) move away from the rather "narrow" definition of "bank defaults" used in previous studies and, instead, consider different shades of bank distress. This takes into account the fact that outright bank failures are very rare in German banking and that distress events (or default events by definition) can be ordered according to severity. Hence, a partial proportional odds model is applied as the superior method in the class of ordered logit models.

The aim of this paper is to make three contributions towards the further development of bank rating models. The first is to explain the supervisory assessment of a bank's soundness, as opposed to distress or default events. Henceforth, we use a unique risk profile dataset, containing supervisory grading, which is divided into four categories A, B, C, and D, where A is the best and D the worst grading. As, by definition, the classes are ordinally scaled, we use a partial proportional odds model (PPOM) which is best practice in regression models with ordinal dependent variables. The partial proportional odds specification allows both intercepts and slope coefficients of estimated hazard functions to differ across classes and, hence, accounts for the relative importance of a bank's quantitative and qualitative factors (Williams, 2006; Kick and Koetter, 2007). To our knowledge, this is the first time an ordered logit specification has been applied to a dataset on supervisory grading for the German banking sector.

The second is to include ("soft") qualitative factors in the regression model in addition to the quantitative CAMEL (**C**apitalization, **A**sset Quality, **M**anagement, **E**arnings, and **L**iquidity) covariate vector which is common in bank rating models. [1] The qualitative factors are taken from the supervisor's partial grading of an institution's internal governance, internal capital adequacy assessment process (ICAAP), interest rate risk, and other qualitative risk categories. We find that qualitative factors are highly significant in the PPOM regression statistics, and they make an important contribution to explaining the supervisor's final assessment of an institution. That is, pseudo R-squared increases from 22.13% to 35.43% when including qualitative partial grading variables in the model. Moreover, we find evidence that supervisors have become more conservative in their final judgement at the beginning of the crisis, that is the risk assessment by the supervisor seems to be more forward-looking than the mere numbers. A reasonable categorization and the forward-looking character of the risk profiles is also confirmed by validation with additional distress information (i.e. information on passive bank mergers, bank moratoria or banks requiring capital support from the deposit insurance schemes) that is available at the Deutsche Bundesbank.

The third contribution of the paper is to introduce a rating tool for banking supervision to ensure equal standards in the assessment of individual banks. The rating tool gives information on how an "average" supervisor would rate a given bank taking into account quantitative factors (taken from supervisory accounting data) and qualitative factors (taken from partial grading). We find that the PPOM assigns roughly two thirds of the banks to exactly the same rating class as the supervisor,

[1] To our best knowledge studies on bank rating models in Germany have been based on purely quantitative information. Other CAMEL rating systems, however, are defined in a way to include qualitative elements. For example, the US supervisory CAMELS ratings, which is used by authorities like the Fed, the FDIC, or the OCC, is based on quantitative financial statements of the banks and qualitative information from on-site inspections by the regulators.

and more than 99% to the same or a neighboring rating class.

The remainder of this paper is organized as follows: After the introduction in Section 1, Section 2 summarizes the institutional set-up of banking supervision in Germany and gives a description of the databases. The empirical model is presented in Section 3. Major findings are discussed in Section 4, in Section 5 the supervisory risk assessment is validated with additional distress information, and Section 6 concludes.

2. Institutional background

2.1. Banking supervision in Germany

The German banking sector comprises three pillars of universal banks: commercial, savings and cooperative banks. The primary legal basis for banking supervision is the German Banking Act (*"Kreditwesengesetz, KWG"*), which lays down rules for banks designed to prevent adverse developments jeopardizing the functioning of the banking system. Accordingly, it is most important that institutions have adequate capital and liquidity and have installed adequate risk control mechanisms. In Germany banking supervision is shared by the Federal Financial Supervisory Authority (*"Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin"*) and the German central bank (*"Deutsche Bundesbank, BBK"*) (Carletti et al., 2008).

The Deutsche Bundesbank is responsible for ongoing monitoring pursuant to section 7 (1) of the Banking Act. This comprises in particular the ascertainment of facts, the analysis of information, and the evaluation of current and potential risks. The Bundesbank clarifies any discrepancies regarding documents and supervisory reporting with the institutions, and it has the right to demand information pursuant to section 44 (1) sentence 1 of the Banking Act. Part of its ongoing monitoring is analyzing and evaluating the information received, in particular that contained in the documents filed by institutions, auditors' reports as per section 26 of the Banking Act, and annual financial statements. The Bundesbank summarizes the findings of its ongoing monitoring in the risk profile, which includes in particular an evaluation of an institution's risks, its organization and internal control procedures, and an assessment of its risk-bearing capacity. The Bundesbank makes the results and evaluations from its ongoing monitoring available to BaFin (Deutsche Bundesbank and BaFin, 2008).

BaFin is responsible for the final summary and forward-looking assessment of whether the institutions' risks are matched by their policies, strategies, procedures, mechanisms guaranteeing sound risk management, and capital. BaFin will normally base its supervisory measures on the audit, findings, and evaluations made by the Bundesbank in the course of its ongoing monitoring. Final assessment and decision-making power on all supervisory measures (including in particular general orders and administrative acts), questions of interpretation, and decisions in respect of the supervision schedule rest with BaFin. Therefore, after consulting the Bundesbank, BaFin has the final say on the compatibility of concrete or abstract facts with the relevant legal norms, notices, circulars or other supervisory regulations. Regarding supervisory activities in advance of and during the implementation of serious supervisory measures, particularly close coordination between BaFin and the Bundesbank has been agreed (Deutsche Bundesbank and BaFin, 2008).

2.2. *Risk profile definition*

The primary basis for the institutions' supervisory assessment is the *risk profile* which comprises an evaluation of all of an institution's risks, its organization and internal control procedures and its risk-bearing capacity. The risk profile is compiled by the Bundesbank at least once a year (and updated in the event of new material information) and passed on to BaFin for approval and any decision that needs to be made. The evaluations and classifications carried out by the Bundesbank and summarized in the risk profile enable BaFin (supported by the Bundesbank if necessary) to assess the need for supervisory action or to collect further information (Deutsche Bundesbank and BaFin, 2008). [2]

[2] For a detailed description of the division of responsibilities between BaFin and the Deutsche Bundesbank see Deutsche Bundesbank and BaFin (2008).

3. Methodology and data

Eventually, any risk profile is classified into a category A, B, C, or D, where A represents the best class and D indicates substantial problems. In the further analysis we will use bank-individual risk profiles of commercial, savings, and co-operative banks for the years 2006 through 2008.[3] To our knowledge, this is the first time this database has been used in banking supervision research.

The ordered nature of this risk profile data requires the application of ordered regression techniques when aiming at its explanation. In Kick and Koetter (2007) a detailed discussion of ordered logit (OLT), generalized ordered logit (GOLT), and partial proportional odds models (PPOM) is given, and respective bank rating models based on the Bundesbank's distress database and on a purely quantitative CAMEL covariate vector are specified. The authors show that there are large differences in the institutions' probabilities of distress when PPOM instead of simple OLT models are applied, where the former is, based on theoretical considerations, the superior model specification (Williams, 2006). In the present study we therefore base our analysis exclusively on the partial proportional odds methodology.

An ordered logit model estimates the probability P that the ordinal risk profile RP of bank i takes on the value $j = 1,..,M$, where M is the number of classes, X_i is a vector of explanatory variables for bank i,

$$P(RP_i > j) = g(\alpha_j + \beta X_i) = \frac{exp(\alpha_j + \beta X_i)}{1 + exp(\alpha_j + \beta X_i)}\ , \quad \text{for } j = 1,2,..,M-1, \qquad (1)$$

and α_j and β are parameters to estimate.[4]

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[3] Large private banks ("big five"), Landesbanken, and central credit cooperatives are dropped from the database because of their heterogeneity and different profile.

[4] In the remainder of the paper P(RP_i>j) is denoted as P_i(A), P_i(B), P_i(C), and P_i(D), where A, B, C, and D are risk profile categories.

In the ordered logit model the so-called "parallel lines" (or "proportional odds") assumption is made. Hence, in equation (1) only the cut-off parameters α_j differ across risk profile categories, while the slope parameters of the link function are assumed to be identical. Hence, a change in the CAMEL covariates is expected to have almost the same effect on the four risk profile categories A, B, C, and D. As the categorization of the ordinal risk profile reflects increasing severity, the j hazard function intercepts α_j exhibit increasingly large negative values (Greene, 2003).

Williams (2006) suggests the use of a generalized ordered logit or a partial proportional odds model instead of the standard ordered logit. Both models allow not only for intercepts, but also for (selected) slope coefficients to differ between risk profile categories. While the GOLT specification allows the greatest flexibility as all intercepts and slope coefficients for all explanatory variables are estimated for each risk profile category individually, in the PPOM selected slope coefficients are kept constant when they do not violate the proportional odds assumption. Especially for slope coefficients which differ only slightly over risk profile categories a parallel lines constraint seems to be reasonable, while other coefficients should be allowed to vary over risk profile categories. Therefore, specifying the PPOM we explicitly test for which explanatory variables the proportional odds assumption holds and for which variables this assumption is violated. [5]

$$P(RP_i > j) = g(\alpha_j + \beta_j X_i) = \frac{exp(\alpha_j + \beta_j X_i)}{1 + exp(\alpha_j + \beta_j X_i)}, \quad \text{for } j = 1, 2, .., M-1. \qquad (2)$$

[5] For estimating the regression model we apply the "gologit2" routine in the software package Stata (Williams, 2006).

The respective probabilities that RP_i will take on values $j = 1,..,M$ are given by

$$P(RP_i = 1) = 1 - g(\alpha_1 + \beta_1 X_i), \tag{3a}$$
$$P(RP_i = j) = g(\alpha_{j-1} + \beta_{j-1} X_i) - g(\alpha_j + \beta_j X_i), \text{ for } j = 2,..,M-1, \tag{3b}$$
$$P(RP_i = M) = g(\alpha_{M-1} + \beta_{M-1} X_i). \tag{3c}$$

To estimate probabilities for the respective risk profile categories, the risk profile of a bank is explained by quantitative and qualitative variables. First, *quantitative factors* are specified by standard quantitative CAMEL components which are chosen on the basis of previous evidence in the literature, the assessment of practitioners at the Bundesbank, data availability, as well as statistical properties. The model optimization process includes univariate binary logit regressions for each risk profile category (versus the other categories) and a variable selection process based on discriminatory power (AUR), goodness of fit (pseudo R^2), correlations amongst the regressors, etc. [6]

Second, in this study we pay special attention to *qualitative factors* determining a bank's supervisory risk profile. Using the supervisor's partial grading on individual risk categories, which are also classified A, B, C, or D, we include dummies for banks' internal governance, internal capital adequacy assessment process (ICAAP), interest rate risk, and other qualitative risk components in the regressions. For the first (and most important) three risk components partial rating classes C and D are modeled separately, while for the other qualitative components [7] one dummy variable for categories C and D is specified. A finer modeling of the qualitative risk profile factors would cause near collinearity amongst the regressors. [8] We also in-

[6] The variable selection process is in line with other bank rating and bank distress studies, such as Porath (2006), and Kick and Koetter (2007).

[7] The dummy variable *D_OTHER_CD* takes "1" if an institution is rated in one of the following qualitative risk components as C or D: *equity investment risk*, *ownership structure risk*, *liquidity risk*, *operational risk*, *other market risk*, *other material risk*.

[8] As *gologit2* is extremely sensitive to model misspecification (resulting in problems such

clude banking group dummies in our regressions, but we do not show regression statistics for confidentiality reasons. Summary statistics of the quantitative CAMEL covariate vector are depicted in Table 1 while the summary statistics of the risk profiles (total and partial grading) are also confidential and, hence, not revealed in this paper. [9]

Table 1
Summary statistics of quantitative CAMEL covariates
This table presents descriptive statistics for regulatory data obtained from the Bundesbank. The sample comprises 5,181 observations on up to 1,762 banks that were subject to regulatory risk profile assessment during the 2006 – 2008 period. Except for the dummies all variables are measured as percentages.

Variable	Mean	Std. dev.	Min	Max
Equity ratio	11.36	4.54	5.44	40.44
Bank reserves ratio	2.16	1.10	0.00	5.06
Dummy hidden liabilities	0.16	0.37	0.00	1.00
Customer loans ratio	57.28	14.17	11.66	93.43
NPL ratio	5.61	3.76	0.20	23.90
Cost-income ratio (CIR)	68.74	10.43	36.89	120.36
Return on equity (RoE)	9.30	8.10	-26.82	33.22
Total assets growth	2.08	5.42	-12.08	30.64
D_IGOV_C			restricted	
D_IGOV_D			restricted	
D_ICAAP_C			restricted	
D_ICAAP_D			restricted	
D_INTEREST_C			restricted	
D_INTEREST_D			restricted	
D_OTHER_CD			restricted	
Observations			5,181	

Quantitative: Equity ratio = Tier 1-capital to risk-weighted assets / Bank reserves ratio = Reserves according to section 340f of the German Commercial Code to total assets / Dummy hidden liabilities = Indicator for banks with avoided write-offs / Customer loans ratio = Customer loans to total assets / NPL ratio = Non-performing loans to customer loans / Cost-income ratio (CIR) = Total administrative expenses to operating result / Return on equity (RoE) = Operating result to equity / Total assets growth = Growth of deflated total assets. *Qualitative:* D_IGOV_C = Dummy internal governance (C) / D_IGOV_D = Dummy internal governance (D) / D_ICAAP_C = Dummy internal capital adequacy assessment process (C) / D_ICAAP_D = Dummy internal capital adequacy assessment process (D) / D_INTEREST_C = Dummy interest rate risk (C) / D_INTEREST_D = Dummy interest rate risk (D) / D_OTHER_CD = Dummy other qualitative risk categories (C and D).

as negative probabilities or a failure in convergence of the estimation technique), on the one hand we have to be careful in including variables but, on the other hand, we can be quite sure that our final model is well specified.

9 A moderate outlier treatment is applied to the dataset, i.e. except for the dummy variables all covariates are truncated at the 1^{st} and 99^{th} percentile.

We determine capitalization by *Equity ratio*, *Bank reserves ratio*, and *Dummy hidden liabilities* as an indicator for avoided write-offs. Moreover, *Customer loans ratio* and *NPL ratio* measure the quality of a bank's credit portfolio, while *CIR* is used to proxy management efficiency. An institution's profitability and growth capabilities are determined by *RoE* and *Total assets growth*. We do not include any quantitative measure for liquidity as such a variable cannot reliably be determined with the data available at the Deutsche Bundesbank; see also Porath (2006).

For our empirical analysis, we use supervisory risk profile data as well as data from the Bundesbank's prudential database BAKIS for the years 2006 through 2008. BAKIS is the information system on bank-specific data which is jointly operated by the Deutsche Bundesbank and the BaFin. Having access to this confidential database is essential for our analysis, since information on the supervisory risk profile assessment as well as information from supervisory reporting (such as the level of risk-weighted assets, hidden liabilities, undisclosed § 340f reserves etc.) are not publicly available.

4. Results

4.1. Drivers of bank risk

The results from the partial proportional odds model in equation (2) are depicted in Table 2. Coefficient estimates for both the quantitative CAMEL vector and the qualitative components are in line with expectations and highly significant. Better capitalization and bank reserves, higher profitability and large asset growth increase the likelihood for a bank to be graded in a better risk profile category. On the other hand, avoided write-offs on a bank's assets ("hidden liabilities"), bad loan quality, and management inefficiency, measured by a high cost-income ratio, imply a worse supervisory rating.

More precisely, *Equity ratio* and *CIR* turn out to effect only categories A, B, and C, but they are not eligible to change the supervisory assessment of a problem bank (category D). Yet the *Bank reserves ratio*, the *Dummy hidden liabilities*, the *NPL ratio*, and the *RoE* seem to significantly affect all risk profile categories. The *Customer loans ratio* seems to have an ambiguous influence on the risk assessment: increased business opportunities in the customer loans segment seem to be regarded as beneficial for lower risk profile categories, while a higher customer loans ratio is also associated with more risk-taking which increased the probability for a "C-level-bank" to be considered a "problem bank" by banking supervision. That is, a higher engagement in the more risky customer loans business is eligible to push a bank with a good risk profile (via increased earnings) towards the A-category; for a bad-profile-bank, however, more risk-taking via customer loans has the opposite effect and would worsen the supervisory assessment. [10] Finally, *Total asset growth* loses significance for mid-level rated institutions.

In the PPOM (including quantitative and qualitative factors) parallel lines con-

[10] In Table 2 it can be shown that this result only holds when controlling for all risk factors.

straints are imposed for all coefficients of *Dummy hidden liabilities*, *NPL ratio*, *RoE*, *D_INTEREST_D*, and the two year dummies. In order to test the PPOM for correct model specification regarding the parallel lines assumption, we apply a Wald test, in which we restrict the coefficients of the six variables to be equal across risk profile categories. The insignificant test statistic shown at the bottom of Table 3 (16.35%) strongly indicates that the final model does not violate the proportional odds (or parallel lines) assumption.[11] Hence, we conclude that the models are correctly specified and well suited to base our further analysis upon.

[11] Similarly, in the *PPOM quantitative factors* and *PPOM qualitative factors*, parallel line constraints are imposed to the coefficients of selected variables, and the final models are also confirmed by Wald tests.

Table 2

Regression statistics from the partial proportional odds model (PPOM)

	PPOM			PPOM quantitative factors			PPOM qualitative factors		
Variable	β_1	β_2	β_3	β_1	β_2	β_3	β_1	β_2	β_3
				Quantitative factors (CAMEL vector)					
Equity ratio	-0.1152***	-0.0525***	-0.0262	-0.1040***	-0.1040***	-0.1040***			
	[0.012]	[0.016]	[0.025]	[0.011]	[0.011]	[0.011]			
Bank reserves ratio	-0.6181***	-0.8768***	-1.3506***	-0.6999***	-1.0527***	-1.6349***			
	[0.041]	[0.074]	[0.172]	[0.039]	[0.060]	[0.136]			
Dummy hidden liabilities	0.4825***	0.4825***	0.4825***	0.7054***	0.7054***	0.7054***			
	[0.093]	[0.093]	[0.093]	[0.084]	[0.084]	[0.084]			
Customer loans ratio	-0.0143***	0.0005	0.0179***	-0.0165***	-0.0091***	0.0019			
	[0.003]	[0.004]	[0.006]	[0.003]	[0.003]	[0.006]			
NPL ratio	0.1846***	0.1846***	0.1846***	0.1900***	0.1900***	0.1900***			
	[0.010]	[0.010]	[0.010]	[0.009]	[0.009]	[0.009]			
Cost-income ratio (CIR)	0.0425***	0.0473***	0.0152	0.0408***	0.0408***	0.0408***			
	[0.005]	[0.007]	[0.011]	[0.004]	[0.004]	[0.004]			
Return on equity (RoE)	-0.0312***	-0.0312***	-0.0312***	-0.0458***	-0.0458***	-0.0458***			
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]			
Total assets growth	-0.0291***	0.0060	-0.0379**	-0.0223***	-0.0051	-0.0447**			
	[0.008]	[0.011]	[0.018]	[0.007]	[0.009]	[0.018]			
				Qualitative factors (based on the supervisor's assessment)					
D_IGOV_C	2.8673***	2.1641***	0.3224				2.6099***	1.8829***	0.3402
	[0.429]	[0.226]	[0.292]				[0.373]	[0.204]	[0.252]
D_IGOV_D	3.5887**	4.5669***	2.3649***				2.9747***	3.8566***	2.0756***
	[1.402]	[0.849]	[0.525]				[1.097]	[0.589]	[0.517]
D_ICAAP_C	2.9193***	2.7322***	1.0538***				3.8306***	3.4062***	2.3100***
	[0.548]	[0.174]	[0.249]				[0.515]	[0.161]	[0.221]
D_ICAAP_D	2.0400*	3.8280***	3.7562***				5.4755***	5.4755***	5.4755***
	[1.108]	[0.752]	[0.419]				[0.339]	[0.339]	[0.339]
D_INTEREST_C	2.1828***	1.2783***	0.8907***				2.1694***	1.5271***	1.0840***
	[0.200]	[0.156]	[0.259]				[0.180]	[0.139]	[0.217]
D_INTEREST_D	1.2060***	1.2060***	1.2060***				1.6348***	1.6348***	1.6348***
	[0.351]	[0.351]	[0.351]				[0.326]	[0.326]	[0.326]
D_OTHER_CD	0.9559***	1.4783***	1.6122***				0.9930***	1.5809***	1.6179***
	[0.158]	[0.164]	[0.238]				[0.137]	[0.152]	[0.223]
				Year dummies and constant					
D_Y2007	-0.0967	-0.0967	-0.0967	-0.2391***	-0.2391***	-0.2391***	0.0675	0.0675	0.0675
	[0.078]	[0.078]	[0.078]	[0.074]	[0.074]	[0.074]	[0.066]	[0.066]	[0.066]
D_Y2008	0.1770**	0.1770**	0.1770**	-0.0460	-0.0460	-0.0460	0.0694	0.4648***	0.4552**
	[0.089]	[0.089]	[0.089]	[0.082]	[0.082]	[0.082]	[0.075]	[0.120]	[0.226]
Constant	-0.6954	-7.0276***	-8.2399***	0.3357	-2.8781***	-5.5523***	-0.1960	-3.7244***	-5.8669***
	[0.482]	[0.747]	[1.181]	[0.445]	[0.472]	[0.577]	[0.138]	[0.280]	[0.399]
Observations		5,181			5,181			5,181	
Pseudo R-squared		0.3543			0.2213			0.2307	
Wald chi2 (45) / (22) / (27)		1,868.38			1,677.32			1,281.99	
Log pseudolikelihood		-3,826.17			-4,614.06			-4,558.26	

Robust standard errors in parentheses; ***,**,* denote significance at the 1,5,10 percent level, respectively.

Table 3
Wald test of parallel lines assumption
An insignificant test statistic indicates that the final model does not violate the proportional odds/ parallel lines assumption.

	PPOM	PPOM quantitative factors	PPOM qualitative factors
Wald chi2 (12) / (14) / (6)	16.64	19.36	5.89
Prob > chi2	0.1635	0.1517	0.4355

One crucial finding from our study is the high significance of the qualitative variables in the regressions. Table 2 shows that the pseudo R-squared increases from 22.13% to 35.43% when including qualitative partial grading variables. At the same time, a regression including *only* qualitative factors (right columns in Table 2) shows a pseudo R-squared of 23.07%, and we find that qualitative information on a bank's internal governance, ICAAP, interest rate risk, and other qualitative risk categories strongly impair a bank's supervisory risk profile. We interpret this as strong evidence for the dominance of quantitative *AND* qualitative risk assessment over a purely quantitative CAMEL rating approach. This finding is highly policy relevant, as it means that any supervisory and financial stability assessment which is solely based on a quantitative CAMEL rating, lacks important qualitative information. Therefore, on-site inspections as carried out by the Deutsche Bundesbank and the BaFin are essential for a comprehensive risk assessment in the banking industry.

Regarding individual coefficients in the PPOM three comparisons are made: (1) risk profile category A is compared with categories B, C, and D, (2) A and B are contrasted to C and D and (3) A, B, and C are regarded relative to D. For example, a coefficient β_1 for *Equity ratio* of -0.1152 implies that higher capitalization increases the probability for category A, and decreases the probability for the remaining categories. Likewise, a β_2 for *Equity ratio* of -0.0525 increases the probability of A and B and implies a lower probability for C and D. Finally, β_3 turns out to be insignificant for the *Equity ratio*. [12]

Finally, the significant and positive time-dummy-coefficient for 2008 indicates that, compared to the year 2006, supervisors have become more conservative in their final judgement during the crisis. This finding, however, only holds when controlling for all relevant risk factors, i.e. for *quantitative* and *qualitative* components. In other words, while the mere numbers not yet indicate a crisis, the final results of the on-site inspections already do. The regulators hereby add a forward-looking perspective to the backward-looking accounting data. Therefore, our analysis indicates that the regulatory assessment has become more conservative under deteriorating market conditions at the beginning of the crisis. Remarkably, in 2007 the purely quantitative factors imply significantly better risk profiles then in 2006, while supervisors were already concerned.

For a more detailed assessment of the effects we transform regression coefficients to odds ratios by $OR_k = \exp(\beta_k)$, for k = 1, 2, 3 (cf. Table 4).

Odds ratios approximate "relative risks". For example, an increase of the *NPL ratio* by one percentage point increases the probability for a bank to be graded into a worse risk profile category by 20.28%; as the odds ratio is constant over all three risk profile categories, this result holds for (1) A vs. B, C, D, and (2) A, B vs. C, D, and (3) A, B, C vs. D. On the other hand, an increase in the *Equity ratio* by one percentage point increases the probability for (1) A vs. B, C, D by 10.88%, and (2) A, B vs. C, D by 5.1%, while the probability for (3) A, B, C vs. D remains almost unaffected.

[12] In order prove the robustness of the model coefficients over time, we split the sample and run regressions for the PPOM by years. Statistics are reported in Table 8 in the appendix.

Table 4
Odds ratios from the partial proportional odds model (PPOM)
This table presents odds ratios from the partial proportional odds model, which are used to approximate “relative risks”.

		PPOM	
Variable	OR_1	OR_2	OR_3
		Quantitative factors (CAMEL vector)	
Equity ratio	0.8912***	0.9489***	0.9741
Bank reserves ratio	0.5389***	0.4161***	0.2591***
Dummy hidden liabilities	1.6202***	1.6202***	1.6202***
Customer loans ratio	0.9858***	1.0005	1.0180***
NPL ratio	1.2028***	1.2028***	1.2028***
Cost-income ratio (CIR)	1.0435***	1.0485***	1.0154
Return on equity (RoE)	0.9693***	0.9693***	0.9693***
Total asset growth	0.9713***	1.0060	0.9628**
		Qualitative factors (based on the supervisor’s assessment)	
D_IGOV_C	17.5891***	8.7071***	1.3805
D_IGOV_D	36.1852**	96.2481***	10.6425***
D_ICAAP_C	18.5278***	15.3668***	2.8685***
D_ICAAP_D	7.6903*	45.9697***	42.7876***
D_INTEREST_C	8.8710***	3.5904***	2.4370***
D_INTEREST_D	3.3402***	3.3402***	3.3402***
D_OTHER_CD	2.6011***	4.3854***	5.0138***
		Year dummies	
D_Y2007	0.9079	0.9079	0.9079
D_Y2008	1.1936**	1.1936**	1.1936**
Observations		5,181	

Robust standard errors in parentheses; ***,**,* denote significance at the 1,5,10 percent level, respectively.

In the context of the qualitative risk dummies, odds ratios indicate how many times higher the probability is of a bank being assigned to a worse risk profile category when the dummy changes from zero to one. Again, we find strong evidence that a bank’s risk profile is strongly influenced by its internal governance and internal capital adequacy assessment process. When, for example, the supervisor assigns a D for internal governance the probability is 96.25 times as large for risk profile C, D than for A, B, and 10.64 times as large for D than for A, B, C. We find similar results when for ICCAP the worst rating class is assigned, as well as for interest rate risk and other qualitative risk categories, but here at a lower significance. [13]

[13] Note that this quantification of “relative risks” is just an approximation as this interpre-

Furthermore, marginal effects are employed to evaluate the economic significance of individual covariates. We report marginal effects for each risk profile category, evaluated at the mean of the respective regressor. [14]

tation for odds ratios only holds when they are "small numbers".

[14] Regression coefficients may be misleading since they are sensitive to measurement units. Therefore, inference in regression analysis should also be based on marginal effects (Hosmer and Lemshow, 2000).

Table 5
Marginal effects for the partial proportional odds model (PPOM)
This table presents marginal effects from the partial proportional odds model, which are calculated as elasticities $\delta ln(P)/\delta lnx$.

	PPOM			
Variable	β_1	β_2	β_3	β_4
		Quantitative factors (CAMEL vector)		
Equity ratio	0.9580***	-0.3263***	-0.5620***	-0.2966
	[0.101]	[0.044]	[0.171]	[0.286]
Bank reserves ratio	0.9769***	-0.1848***	-1.6717***	-2.9034***
	[0.069]	[0.035]	[0.155]	[0.372]
Dummy hidden liabilities	-0.0570***	0.0145***	0.0712***	0.0775***
	[0.011]	[0.003]	[0.014]	[0.015]
Customer loans ratio	0.6010***	-0.2508***	-0.0327	1.0184***
	[0.131]	[0.056]	[0.242]	[0.370]
NPL ratio	-0.7583***	0.1933***	0.9470***	1.0314***
	[0.046]	[0.020]	[0.051]	[0.054]
Cost-income ratio (CIR)	-2.1407***	0.5078***	3.1013***	1.0429
	[0.244]	[0.102]	[0.434]	[0.746]
Return on equity (RoE)	0.2122***	-0.0541***	-0.2650***	-0.2887***
	[0.033]	[0.010]	[0.042]	[0.045]
Total assets growth	0.0443***	-0.0197***	0.0166	-0.0786**
	[0.012]	[0.005]	[0.022]	[0.037]
		Qualitative factors (based on the supervisor's assessment)		
D_IGOV_C	-0.1288***	0.0378***	0.1279***	0.0197
	[0.020]	[0.008]	[0.014]	[0.018]
D_IGOV_D	-0.0466**	0.0099	0.0764***	0.0418***
	[0.019]	[0.006]	[0.015]	[0.009]
D_ICAAP_C	-0.1901***	0.0504***	0.2308***	0.0933***
	[0.038]	[0.013]	[0.015]	[0.022]
D_ICAAP_D	-0.0375*	0.0044	0.0879***	0.0938***
	[0.021]	[0.007]	[0.018]	[0.010]
D_INTEREST_C	-0.1570***	0.0502***	0.1170***	0.0871***
	[0.016]	[0.006]	[0.015]	[0.025]
D_INTEREST_D	-0.0102***	0.0026***	0.0128***	0.0139***
	[0.003]	[0.001]	[0.004]	[0.004]
D_OTHER_CD	-0.0705***	0.0119**	0.1354***	0.1617***
	[0.012]	[0.005]	[0.016]	[0.024]
		Year dummies		
D_Y2007	0.0237	-0.0060	-0.0296	-0.0323
	[0.019]	[0.005]	[0.024]	[0.026]
D_Y2008	-0.0421**	0.0107**	0.0526**	0.0573**
	[0.021]	[0.005]	[0.026]	[0.029]
Observations		5,181		

Robust standard errors in parentheses; ***,**,* denote significance at the 1,5,10 percent level, respectively.

Marginal effects differ across risk profile categories.[15] Table 5 shows marginal effects calculated as elasticities $\delta ln(P)/\delta ln(x)$. For example, a 1%-increase from the mean *Equity ratio* implies a rise in the probability of risk profile category A by 0.96%. Likewise, for qualitative factors elasticities measure the percentage probability-change for the respective profile category in contrast to a 1%-change in the dummy. As the mean-dummies are just a (rather small) fraction of one, the marginal effects of qualitative variables on probabilities of rating classes are not too high. A 1%-increase in the internal governance dummy of category D (D_IGOV_D), for example, would decrease P(A) by roughly 0.05%.

4.2. Constructing bank scores

Finally, we compare three PPOM specifications, one including and one without qualitative factors, in still another way. We calculate probabilities according to equation (2) and derive a bank-individual score based on the formula:

$$Score_i = 1 \cdot P_i(A) + 2 \cdot P_i(B) + 3 \cdot P_i(C) + 4 \cdot P_i(D). \quad (4)$$

Assuming a linear relationship over risk profile categories, we assign classes A (1.0 - 1.5), B (1.5 - 2.5), C (2.5 - 3.5), and D (3.5 - 4.0). This procedure is valid as probabilities for categories A - D add up to one and they are not more than double-peaked over categories, i.e. the largest probability is either concentrated in only one, or in two neighboring classes. Therefore, the model score is more detailed than the supervisory categorization as, for example, the supervisor has to decide on *category B or C*, while the model outcome can also be an intermediate result such

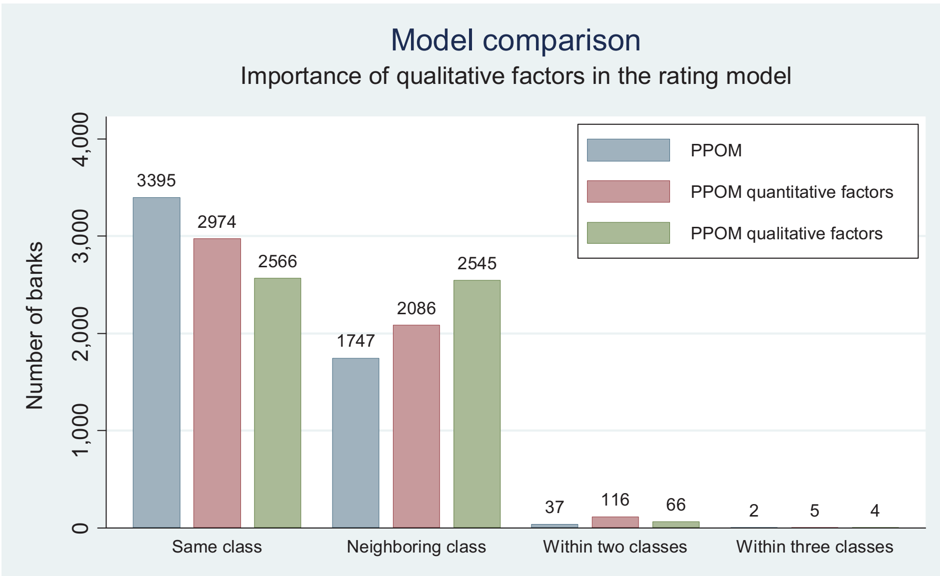
[15] From equation (2) we see that the probability of each risk profile category also depends on the respective α_j. Hence, we get different probabilities across categories even when estimating a standard ordered logit model or when in the PPOM parallel lines restrictions are applied.

as 2.5 (category B - C).

In this comparison we use the supervisory risk profiles as a benchmark. For the model including qualitative factors we find that the rating tool assigns roughly two thirds of the banks to exactly the same rating class as the supervisor, and more than 99% to the same or a neighboring rating class. The PPOM grading differs by two (three) classes from the supervisory risk assessment in only 0.71% (0.04%) of all cases. [16] Unfortunately, for confidentiality reasons, the distribution of scores must not be shown.

Figure 1 illustrates how the three models *PPOM* (quantitative and qualitative factors), *PPOM quantitative factors* and *PPOM qualitative factors* agree with the supervisory risk assessment. [17]

Figure 1. Model comparison



[16] As already indicated in the regression statistics in Table 2 by a pseudo R-squared of 35.43% for the *PPOM* including qualitative and quantitative factors (vs. 22.13% for the *PPOM with quantitative factors* and 23.07% for the *PPOM with qualitative factors*), the comprehensive PPOM specification allows the best assignment of the risk profiles.

[17] Note that the two outlier observations in the PPOM turned out to be data errors.

5. Validation of supervisory risk assessment with additional bank distress information

Finally, banks' supervisory risk assessment is validated with additional bank distress information that is available at the Deutsche Bundesbank. More precisely, the data used in the validation process is information on banks' need for (*i*) capital support from the deposit insurance schemes, (*ii*) information on passive mergers, and (*iii*) information on bank moratoria. Banks requiring capital support can be considered severely troubled such as banks being rescued in a restructuring merger. [18]

In order to address the issue that risk profiles are finalized by Bundesbank and BaFin by mid of the subsequent year (i.e. the risk profiles for 2008 are finalized by mid 2009) we do not only report distress information for the respective year, but we also report forward looking data. This is to assure that the supervisor is mostly not yet aware of those signals when deciding upon the risk profile of a bank.

In Table 6 we hereby express each of the distress indicators - such as capital support by the insurance scheme, passive bank mergers, and bank moratoria - as a percentage share of the observations in the respective risk profile category. [19]

[18] We hereby focus on passive mergers as an additional indicator for bank distress, as we can assume that a large part of the banks being taken over in such a merger were too weak to exist alone in the market. Nevertheless, there might be some bank mergers which took place for other reasons, in particular economies of scale, efficiency considerations, diversification strategies, increasing market power, etc.

[19] Note that in Table 6 for statistics I, III, IV, and V data until 2009 is available, while for statistics II the information can only be shown until 2008.

Table 6
Validation of supervisory risk assessment
This table presents several bank distress indicators as a percentage of the observations in the respective risk profile category.

Category	**I**	**II**	**III**	**IV**	**V**
A	0.28%	0.41%	1.56%	0.00%	0.00%
B	0.82%	0.71%	1.59%	0.00%	0.00%
C	3.28%	4.12%	2.53%	0.00%	0.30%
D	13.73%	11.67%	6.67%	1.96%	0.39%
Observations	5,181	3,497	5,181	5,181	5,181

I. Capital support in the current year

II. Capital support in the subsequent year

III. Passive merger in the subsequent year

IV. Capital support in the current year, and passive merger in the subsequent year

V. Moratorium in the subsequent year

We find a positive relationship between the respective distress indicators and the worse risk profile categories. That is, the supervisor seems to be able to identify banks which are likely to face a severe distress event in the near future. We interpret this result as additional evidence for a reasonable and forward-looking categorization of the risk profiles.

6. Conclusion

This paper proposes a partial proportional odds model (PPOM) to explain banks' supervisory risk profiles. The risk profile comprises an evaluation of an institution's risks, its organization and internal control procedures, and its risk-bearing capacity. It is divided into twelve partial grades comprising quantitative and qualitative criteria. We use a unique database on the institutions' supervisory risk profiles for the years 2006 through 2008. In line with previous bank rating studies, a bank-specific CAMEL vector of quantitative financial profile components is specified. Additionally, we enrich our model by qualitative factors which are determined in bank-individual on-site inspections.

In our model, qualitative factors turn out to have a highly significant explanatory power for the final risk profile. Pseudo R-squared increases from roughly 22.1% to almost 35.5% when including qualitative partial grading variables. That is, qualitative information on a bank's internal governance, ICAAP, interest rate risk, and other qualitative risk components play an equally important role as the purely quantitative CAMEL covariate vector. When validating risk profiles with further distress information that is available at the Deutsche Bundesbank (like capital support from the deposit insurance schemes as well as information on passive mergers and bank moratoria), we find a positive relationship between the respective distress indicators and the worse risk profile categories. That is, the supervisor seems to be able to identify banks which are likely to face a severe distress event in the near future, which is some indication for a reasonable and forward-looking categorization of the risk profiles.

Furthermore, we find evidence that supervisors have become more conservative in their final judgement at the beginning of the crisis. Hereby most interesting, however, is that while in 2008 the *quantitative* numbers do not yet indicate a crisis, the on-site inspections already do. That is, the risk assessment by the supervisor seems to be more forward-looking than the mere numbers. Finally, our rating model assigns roughly two thirds of the banks to exactly the same rating class as the supervisor, and more than 99% to the same or a neighboring rating class. The PPOM grading differs by only two (three) classes from the supervisory risk assessment in only 0.71% (0.04%) of all cases.

In summary, we find that *quantitative* and *qualitative* risk assessment are similarly important when it comes to assess the soundness of financial institutions. This result underpins the importance of bank-individual on-site risk assessment as it is carried out by the Deutsche Bundesbank and the BaFin.

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Appendix: Additional statistics

Table 7

Correlations amongst regressors

This table shows correlations amongst regressors. Note that correlations appear to be quite small and, therefore, multicollinearity should not cause problems in the regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Equity ratio	1																
Bank reserves ratio	0.0243	1															
Dummy hidden liabilities	0.0101	-0.2338	1														
Customer loans ratio	-0.3889	0.0562	-0.199	1													
NPL ratio	-0.016	-0.1004	0.0742	-0.1064	1												
Cost-income ratio (CIR)	0.0672	-0.2019	0.1851	-0.1172	0.0103	1											
Return on equity (RoE)	-0.1246	0.1742	-0.1731	0.027	-0.0055	-0.4371	1										
Total assets growth	0.0436	-0.1492	-0.0032	-0.015	-0.1449	-0.0778	0.0751	1									
D_IGOV_C	-0.0197	-0.1309	0.0889	-0.0331	0.1221	0.0564	-0.0912	-0.0085	1								
D_IGOV_D	-0.0127	-0.1335	0.0443	-0.0382	0.1525	0.0774	-0.0983	-0.0543	-0.0344	1							
D_ICAAP_C	-0.0607	-0.2594	0.1578	-0.0095	0.1654	0.139	-0.1269	-0.013	0.3155	0.0709	1						
D_ICAAP_D	-0.0556	-0.195	0.1309	-0.0541	0.2567	0.1159	-0.1005	-0.0703	0.0927	0.455	-0.0501	1					
D_INTEREST_C	-0.0418	-0.1309	0.1602	-0.1061	0.0431	0.0914	-0.1077	-0.0396	0.102	0.0735	0.1656	0.0922	1				
D_INTEREST_D	-0.0377	-0.1112	0.1095	-0.0639	0.0455	0.0705	-0.0841	-0.0438	0.0926	0.0947	0.0929	0.2249	-0.0357	1			
D_OTHER_CD	0.0482	-0.1713	0.1425	-0.0539	0.064	0.0941	-0.2032	0.0273	0.1335	0.1881	0.1814	0.1513	0.0662	0.0717	1		
D_Y2007	-0.1124	0.0216	-0.0203	0.0143	-0.0281	0.1409	0.0279	-0.1041	-0.0113	0.0005	0.0179	0.0063	0.0183	-0.0043	-0.1128	1	
D_Y2008	0.2972	0.0023	0.137	-0.062	-0.1025	0.1926	-0.1847	0.1724	-0.0298	-0.0215	-0.0721	-0.0639	-0.0172	-0.0019	0.1949	-0.4928	1

Table 8

Regression statistics from the partial proportional odds model (PPOM) by years

	PPOM 2006			PPOM 2007			PPOM 2008		
Variable	β_1	β_2	β_3	β_1	β_2	β_3	β_1	β_2	β_3
					Quantitative factors (CAMEL vector)				
Equity ratio	-0.1533***	-0.1108***	-0.0298	-0.1809***	-0.0580	-0.0949	-0.0623***	-0.0623***	-0.0623***
	[0.025]	[0.043]	[0.049]	[0.025]	[0.039]	[0.078]	[0.015]	[0.015]	[0.015]
Bank reserves ratio	-0.4901***	-0.6202***	-1.2674***	-0.6182***	-0.8758***	-0.5240	-0.6915***	-0.9462***	-1.8455***
	[0.072]	[0.124]	[0.295]	[0.071]	[0.166]	[0.393]	[0.072]	[0.118]	[0.366]
Dummy hidden liabilities	0.0405	0.0405	0.0405	0.5598***	0.5598***	0.5598***	0.6529***	0.6529***	0.6529***
	[0.186]	[0.186]	[0.186]	[0.179]	[0.179]	[0.179]	[0.135]	[0.135]	[0.135]
Customer loans ratio	-0.0076	0.0015	0.0237*	-0.0123**	-0.0007	0.0533**	-0.0243***	-0.0088	0.0112
	[0.006]	[0.009]	[0.013]	[0.006]	[0.009]	[0.022]	[0.005]	[0.006]	[0.010]
NPL ratio	0.1754***	0.1754***	0.1754***	0.2111***	0.2111***	0.2111***	0.1693***	0.2163***	0.2571***
	[0.016]	[0.016]	[0.016]	[0.019]	[0.019]	[0.019]	[0.022]	[0.024]	[0.042]
Cost-income ratio (CIR)	0.0392***	0.0629***	0.0153	0.0471***	0.0422***	-0.0133	0.0420***	0.0420***	0.0420***
	[0.009]	[0.015]	[0.022]	[0.009]	[0.014]	[0.029]	[0.007]	[0.007]	[0.007]
Return on equity (RoE)	-0.0552***	-0.0793***	-0.0545**	-0.0415***	-0.0030	-0.0557	-0.0378***	-0.0217**	0.0228
	[0.012]	[0.017]	[0.027]	[0.012]	[0.020]	[0.042]	[0.009]	[0.010]	[0.022]
Total assets growth	-0.0342*	0.0169	-0.0187	-0.0254	-0.0196	-0.1959***	-0.0287**	0.0185	-0.0322
	[0.018]	[0.025]	[0.035]	[0.016]	[0.027]	[0.065]	[0.011]	[0.014]	[0.023]
					Qualitative factors (based on the supervisor's assessment)				
D_IGOV_C	3.5179***	1.7800***	0.3617	3.9835***	3.3769***	-0.0866	1.7086***	2.0759***	0.4354
	[0.798]	[0.370]	[0.490]	[1.448]	[0.422]	[0.560]	[0.518]	[0.422]	[0.609]
D_IGOV_D	18.1278***	5.6051***	2.5334***	17.3935***	6.5084***	4.9570***	16.1078***	2.8289**	0.9627
	[0.664]	[1.440]	[0.887]	[1.242]	[1.986]	[0.746]	[0.949]	[1.111]	[1.140]
D_ICAAP_C	3.6402***	3.3501***	1.2255***	15.8234***	3.5712***	2.6715***	1.0842***	1.0842***	1.0842***
	[1.052]	[0.272]	[0.447]	[0.394]	[0.333]	[0.646]	[0.332]	[0.332]	[0.332]
D_ICAAP_D	0.0000	17.4536***	4.1558***	-40.2100***	16.6511***	7.6764***	15.4770***	1.4955*	2.9391**
	[0.000]	[0.774]	[0.605]	[1.667]	[0.549]	[1.176]	[0.777]	[0.868]	[1.463]
D_INTEREST_C	1.7432***	1.0499***	0.9477**	3.1882***	1.4829***	1.1362*	2.0990***	1.5567***	0.9988**
	[0.307]	[0.275]	[0.436]	[0.490]	[0.313]	[0.641]	[0.380]	[0.251]	[0.454]
D_INTEREST_D	0.6493	0.6493	0.6493	16.5684***	1.7223**	0.2902	13.5628***	2.5983***	0.3773
	[0.722]	[0.722]	[0.722]	[0.980]	[0.700]	[0.803]	[0.850]	[0.939]	[0.907]
D_OTHER_CD	3.9762***	2.2570***	1.5993***	2.0114***	2.0114***	2.0114***	0.4716**	1.0919***	1.7705***
	[1.405]	[0.373]	[0.448]	[0.344]	[0.344]	[0.344]	[0.203]	[0.247]	[0.394]
Constant	-0.4406	-8.4768***	-8.8959***	-0.4163	-7.0291***	-9.0985***	-0.2667	-5.3000***	-9.2884***
	[1.047]	[1.765]	[2.212]	[1.033]	[1.558]	[3.197]	[0.753]	[0.887]	[1.223]
Observations		1,760			1,737			1,684	
Pseudo R-squared		0.4065			0.4329			0.3009	
Wald chi2 (44) / (45) / (43)		2,781.38			8,416.62			3,181.44	
Log pseudolikelihood		-1,209.43			-1,110.53			-1,346.79	

Robust standard errors in parentheses; ***,**,* denote significance at the 1,5,10 percent level, respectively.

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