DEUTSCHE
BUNDESBANK

Estimating probabilities of default for German savings banks and credit cooperatives

Daniel Porath

Discussion Paper
Series 2: Banking and Financial Supervision
No 06/2004

Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-1
Telex within Germany 41227, telex from abroad 414431, fax +49 69 5601071

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax No +49 69 9566-3077

ISBN 3-86558-033-5

Abstract

A healthy banking system is a fundamental condition for financial stability. When assessing the riskiness of the banking system, analysts often restrict their focus to large banks. This may create a distorted picture in countries like Germany with fragmented banking systems. In Germany, savings banks and cooperative banks taken together are important players in the market. However, little is known about their default risk. The reason is that these banks usually resolve financial distress within their own organisations, which means defaults are not observable from the outside. In this paper we use a new dataset which contains information about financial distress and financial strength of all German savings banks and cooperative banks. The data have been gathered by the Deutsche Bundesbank for microprudential supervision and have never before been exploited for macroprudential purposes. We use the data to identify the main risk drivers. To this end we estimate a default prediction model (hazard model). A second goal of the paper is to analyse the impact of macroeconomic information for forecasting banks' defaults. Recent findings for the USA have cast some doubt on the usefulness of macroeconomic information for banks' risk assessment. Contrary to recent literature, we find that macroeconomic information significantly improves default forecasts.

Keywords: bank failure, default probability, time-discrete hazard rate

JEL classification: C23, G21, G28

Non-technical summary

There is little evidence on the default risk of German savings banks and cooperative banks, although they constitute an integral part of the German banking system. Our aim is to develop a statistical system which estimates probabilities of default (PDs) for savings banks and cooperative banks. We also try to find evidence for the importance of macroeconomic developments for the estimation of PD. Since we adopt a prudential supervisory perspective, default is defined as any event that jeopardises the bank’s viability as a going concern.

The paper uses a dataset from the Deutsche Bundesbank that combines default events with balance sheet information, audit reports, and macroeconomic variables. The data is used to estimate a discrete hazard model. Hazard models are particularly suited for our purposes because they simultaneously include macroeconomic and microeconomic data.

Our main findings are as follows.

1 The relevant factors for the PD estimation are capitalisation, return, credit risk, market risk and the macroeconomic context.

2 Savings banks and cooperative banks can be assessed with the same model. Savings banks, however, reveal a slightly higher risk sensitivity.

3 Models which rely solely on bank-specific information provide good predictors for the relative risk of a bank, yet they are not able to capture the risk level. The performance of the risk level forecast greatly improves if macroeconomic variables are added to the model.

Nichttechnische Zusammenfassung

Sparkassen und Kreditgenossenschaften spielen eine bedeutende Rolle im deutschen Finanzsystem. Trotzdem gibt es kaum empirische Evidenz über die Ausfallrisiken dieser Bankengruppen. Im vorliegenden Diskussionsbeitrag wird ein statistisches Modell zur Schätzung von Ausfallwahrscheinlichkeiten deutscher Kreditgenossenschaften und Sparkassen vorgestellt. Darüber hinaus wird die Bedeutung makroökonomischer Informationen bei der Schätzung der Ausfallwahrscheinlichkeit untersucht. Da die Untersuchung unter einem bankenaufsichtlichen Blickwinkel stattfindet, gilt als Ausfallereignis jedes Ereignis, das den Bestand eines Instituts gefährdet.

Zur Schätzung wird ein Datensatz der Deutschen Bundesbank verwendet. Er umfasst Ausfall-informationen, Jahresabschlüsse, Prüfungsberichtsauswertungen und makroökonomische Variablen. Den methodischen Rahmen bildet ein diskretes Hazardratenmodell. Hazardraten-modelle sind für die vorliegenden Zwecke besonders geeignet, da sie simultan makroökono-mische und mikroökonomische Informationen einbeziehen.

Die Hauptergebnisse sind:

1. Für die Schätzung von Ausfallwahrscheinlichkeiten sind Faktoren wie Kapitalisierung, Ergebnis, Kreditrisiko, Marktrisiko und gesamtwirtschaftliches Umfeld relevant.

2. Sparkassen und Kreditgenossenschaften können mit demselben Modell bewertet werden. Sparkassen reagieren aber etwas sensitiver auf die Risikofaktoren.

3. Modelle, die allein bankspezifische Variablen enthalten, sind für die Prognose des relativen Risikos gut geeignet, können aber keine Niveaueffekte abbilden. Die Schätzung des Risikoniveaus kann durch die Aufnahme makroökonomischer Variablen deutlich verbessert werden.

Content

Estimating probabilities of default for German savings banks and credit cooperatives[#]

1 Introduction

Banks' defaults have to be taken particularly seriously since they are associated with a potential destabilisation of the financial system through contagion. A healthy banking system is therefore a pivotal point for financial stability. When measuring the default risk of banks, analysts typically focus on big banks. Rating agencies provide ratings for about 40 German banks, mostly private banks and Landesbanken.[1] The Credit Monitor of Moody's KMV includes only publicly listed banks, which in Germany amount to 21 institutions. There is, however, almost no empirical evidence for the default risk of cooperative banks or savings banks[2]. These banking groups are important players in the German market, since they represent roughly 25% of the total assets of all German banks and grant about 35% of all loans to German non-banks[3]. Furthermore, they differ considerably from the banks that rating agencies focus on regarding their ownership structure and business focus (see Schmidt and Tyrell (2004) for an overview of the German financial sector). Obviously, neglecting the default risk of these banking groups can cause a severe bias in the total risk assessment of the banking sector.

From a microeconomic perspective, also, it is desirable to learn more about the risk and the risk drivers of savings and cooperative banks. For example, modern risk control techniques which are permitted under the revised Capital Framework of the Basel Committee on Banking Supervision (Basel II) require that creditors are able to estimate their debtors' probabilities of default (PDs). For private customers and non-financial corporates there is a variety of well-

---

This work is part of a project that I have carried out for the Bundesbank. I wish to thank Stefan Blochwitz, Frank Heid, Thilo Liebig, Frank Rothenhäusler and especially Christoph Memmel for their support and helpful comments.

1 See Moody's Investor's Service (2003). There are only few exceptions: for example, Stadtsparkasse Köln, Deka Bank, DZ Bank and WGZ-Bank.

2 As mentioned above, there are some exceptions, like the Stadtsparkasse Köln which is rated by Moody's. We exclude the Landesbanken, the DZ Bank and the WGZ-Bank when referring to savings banks and credit cooperatives.

3 The figures about the market shares refer to the end of 2003 and were taken from Deutsche Bundesbank (2004).

established methods and a sizeable body of evidence about the main risk drivers. However, comparable literature for savings banks and cooperative banks is virtually non-existent. For savings banks the problem is mitigated in some extent by the fact that credits virtually are publicly guaranteed. However, by July 2005 these guarantees will have been phased out.

The fact that there is so little knowledge about the default risk of savings and cooperative banks may be astonishing at first sight, but it can be explained quite simply by a lack of data due to a German particularity: German savings and cooperative banks usually resolve financial distress within their own organisations. Therefore, public default data for these banking groups is not available. In this paper we are able to present some empirical evidence thanks to the unpublished dataset at our disposal. The dataset covers default data, balance sheet information and supervisory reports for all German banks from 1993 to 2002. It has been gathered by the Deutsche Bundesbank and has never before been exploited for macroprudential risk assessment. We use the data to estimate the individual PDs for savings banks and cooperative banks. This is done with the help of a default prediction model that allows us to identify the main risk drivers. We also use the model to analyse possible structural differences in the default risk between savings banks and cooperative banks.

We further contribute to the literature by assessing how much of the model outcome can be attributed to internal (bank-specific) factors and how much to external factors (macroeconomic developments). This issue is of growing importance since deregulation and increased competition seem to have tightened the link between the riskiness of savings and cooperative banks and macroeconomic developments. In fact, the recent economic downturn, with numerous insolvencies and the collapse of the stock market, has probably had a greater impact on their resilience than ever before in the post-war period: see, eg, IMF (2003). Contrary to this intuition, Nuxoll (2003) finds that macroeconomic information does not improve the forecasts of bank defaults. However, his work is limited to US banks and there is no empirical work for Germany. Since we expect different results for Germany, we use our dataset to analyse the question.

We approach the questions raised in this section with a hazard model. In the past few years, hazard models have become widely used in the literature mainly due to their ability to estimate PDs for different forecast horizons (see the literature overview in section 2). Instead, we avail ourselves of a different characteristic: that hazard models estimate the influence of individual (bank-specific) information and time series (macroeconomic) information simultaneously.

The rest of the paper is organised as follows. In the following section we will briefly review the relevant literature (section 2). Section 3 states the goals more precisely and describes the data. In section 4 we turn to a discussion of the methods and then provide an overview of the methods used for the model specification (section 5). Section 6 and 7 present and evaluate the results of the models. Section 8 concludes.

2 Related literature

Starting from seminal work of Altman (1968) and Beaver (1968), today we can look back at more than three decades of experience in using statistical models to predict defaults. Soon after their introduction these methods were applied to banks, examples being Sinkey (1975), Martin (1977) and Altman (1977). At the beginning, discriminant analysis was the leading method. The drawback to this method is the assumption of normally distributed regressors. As generally financial ratios are not normally distributed, maximum-likelihood methods have been used more frequently since the 1980s (Martin (1977); see also the overview of the literature in Demirgüc-Kunt (1989) and Lennox (1999)). Logit and probit procedures are advantageous not only for statistical reasons but also because they directly estimate PDs.[4]

Logit and probit models and discriminant analyses are all cross-sectional methods. Since the data on bank defaults are typically gathered at different points in time – as is the case here – more recent studies such as Cole, Gunther (1995), Shumway (2001), Estrella et al (2000), Henebry (1996) or Looney et al (1989), favour the use of hazard models. Many authors use the Cox proportional hazard model, which exploits the fact that the default data are available on a daily basis; see, for example, Lane et al (1986), Henebry (1996) or Molina (2002). The advantage of the Cox model is that one can analyse the development of PDs over time. This may be useful for special questions such as those addressed in the paper of Claeys et al (2004), where the timing of the closure of a bank after insolvency is investigated for Russian banks. Instead, we argue that time-discrete hazard models are more adequate for our purposes. The main reason is that bank defaults, although available with daily frequency, can only be interpreted on an annual basis. The following section shows that the supervisory (or internal) act which constitutes the default typically is the result of the balance sheet audit. In most cases the exact timing of the audit or of the default event itself is not driven by economic factors but merely by procedural circumstances. Consequently, only the year of the default gives reasonable information for modelling. See Shumway (2001) and Hamerle et al (2004) for examples of using time-discrete hazard rates as default models.

We mainly use hazard models because they offer the possibility to estimate bank-specific and

---

[4] It was not possible to empirically demonstrate throughout that discriminant analysis performs worse. The results of comparative studies are mixed: Lo (1986) finds no significant differences, whereas Espahbodi

macroeconomic variables simultaneously. There is little evidence on the importance of macroeconomic information for forecasting banks' default, a remarkable exception being Nuxoll (2003). In his paper, Nuxoll explicitly investigates the contribution of macroeconomic and regional economic data to bank-failure models and finds that these variables impair the forecasting power of the model. The findings are explained mainly by data limitations, unstable lag structures due to differences in behaviour among the regional supervisory authorities, and the fact that the economic development is reflected in the bank-specific variables. It should be noted that the data limitations are related to the fact that in the US most indicators, like regional GDP, are available only with a lag of several years. In his study, he therefore uses personal income. We argue that, first of all, it not surprising that regional personal income is reflected in the banks' balance sheets, and therefore does not contribute to the forecast. The reason is that it is a lagged indicator of economic activity.[5] Instead, we use indicators which are better suited. Second, Nuxoll investigates only the discriminative power of the models, ignoring the fit to historical default rates. However, a model with a good discriminative power may perform poorly when predicting the default rate because the discriminative power depends only on the relative risk of the banks and not on the level of the risk. For risk assessment, probabilities of default (PDs) are more adequate than relative risk measures. We therefore analyse the contribution of the macroeconomic information on both the discriminative power and the PD.

(1991) notes that the measures for the power of discriminant procedures are exaggerated. The findings of Lennox (1999) show that maximum likelihood methods have greater power.

5 As mentioned before, Nuxoll uses personal income mainly because of the late observability of US regional data, like GDP. In Germany many macroeconomic and regional data are available earlier than the balance sheet.

3 Probabilities of default, data and lag structure

A PD for a given bank captures the probability that the bank will default within a certain period. If, as customary, the period covers the following year, the mean PD (aggregated across all banks) is an estimator for the default rate of that year. More important, it has to be clarified what exactly is meant by default. Most naturally, one would define default as insolvency. The problem arises from the fact that savings banks and cooperative banks simply do not become insolvent because the deposit guarantee scheme for these banking groups guarantees the going-concern basis, for example with the help of capital preservation measures or by a merger with a healthy institution of the same banking group and region. Therefore we define default (i) as any intervention on part of the supervisory authority, the auditor or the deposit guarantee scheme (disclosure of facts pursuant to section 29 (3) of the Banking Act (BA), moratoriums pursuant to section 46a of the BA, capital preservation measures or also the application for such and restructuring caused by mergers) or (ii) as high losses (losses amounting to 25% of liable capital or a negative operating result in excess of 25% of liable capital).[6] In the Bundesbank's database the default information is available for the years between 1995 and 2002. During that time a triple-digit number of credit cooperatives and savings banks has undergone one of the default events. The exact total number of defaults is confidential Bundesbank information, yet it is higher than in most of the studies cited in section 2.

The dataset for the explanatory variables combines financial information about individual banks with macroeconomic data. Due to the regional restrictions of savings banks we also use regional macroeconomic data. We do not incorporate market information, since the banking groups we focus on are not publicly traded and other market information is hardly available. The macroeconomic time series are gathered by the Federal Statistical Office (*Statistisches Bundesamt*) and the Bundesbank. As mentioned earlier, the financial data is taken from an unpublished Deutsche Bundesbank database which covers balance sheets, profit loss accounts, key figures from the audit report, information about the credit portfolio (credit

[6] The default definition is developed from a supervisory perspective. The prudential supervisory purpose is to prevent insolvencies, so the definition covers all events indicating that the bank is in danger of ceasing to exist as a going concern without outside intervention.

register) etc. Most of the data is observed annually and is available for each year from 1993 on. It should be noted that the Bundesbank collects individual bank data for statistical and supervisory purposes. Therefore, the dataset covers not only all banks but also all financial ratios which are generally used for the risk assessment of a bank. To the best of our knowledge, we are the first to analyse the risk of German savings and cooperative banks with a dataset of similar quality.[7]

In order to add the default information to our dataset we create a dummy variable Y_t that takes the value 1 if a default is observed in the year t + 2 and zero otherwise. Banks that are still in existence after default are eliminated from the sample. The rationale for the two-year lag is that most of the default events are the result of the balance sheet audit. Consequently a default occurring in the year t + 2 has been caused by the financial situation in the year t + 1. One further lag is introduced owing to the forecast horizon of one year.

Table 1: Number of banks and default rates[8]

	Credit cooperatives		**Savings banks**	
Year	Number	Δ Default rate*	Number	Δ Default rate*
1995	2,450		638	
1996	2,358	0.80%	598	-3.09%
1997	2,247	0.04%	586	-0.33%
1998	2,078	-0.43%	581	0.52%
1999	1,872	0.37%	563	-0.86%
2000	1,639	-0.36%	548	1.09%
2001	1,474	0.77%	525	0.81%
2002	1,338	-1.05%	498	-0.10%
Total	15,456		4,537	

* Δ Default rate is the difference between default rate in the current year and the previous year.

Table 1 reports the distribution of the total number of savings banks and cooperative banks. There is an ongoing process of consolidation within both banking groups and the total number of institutions is continuously diminishing. Virtually all exits from the markets are mergers with another bank of the same banking group. Since the number of defaults is confidential, we report the first differences of the default rate series. These figures reveal important fluctuations in risk over time. Most notably, the increased difficulties of the banking sector in recent years are reflected in a peak of the default rate in 2001.

---

7 A detailed overview of the data is given by the respective reporting forms which the banks have to provide and which are published by the Bundesbank (www.bundesbank.de).

8 At the time of the survey (2004) the number of defaults for 2003 was not complete. The total number of institutions is not consistent with the official Bundesbank statistics since the latter still include some

The total number of savings banks' defaults is too small to develop two separate models for both banking groups. Since savings banks and cooperative banks have identical business structures, we specify and estimate an overall model and afterwards review the validity of the overall model for the subpopulations.

institutions which, according to our default definition, have defaulted. A few institutions could not be included in the analysis since they failed to submit returns.

4 Method

Our main rationale for using a hazard model is that it allows to combine microeconomic and macroeconomic information. Since bank defaults are observed annually, we use discrete-time hazard models to estimate PD.

Discrete-time hazard models estimate the hazard rate λ_{it} which gives the PD at time t under the condition that no default has occurred prior to t:

$$\lambda_{it} = \mathrm{P}(T_i = t \mid T_i \geq t;\ \beta X_{it}), \tag{1}$$

where T_i is a random variable that stands for the year when the default of bank *i* occurs, X_{it} is an (nx1) vector of exogenous factors (covariates) and β a (1xn) vector of coefficients. Since for bank insolvencies the realisations of T_i are observed annually, λ_{it} corresponds to the one-year PD.

Hazard models allow a parametric estimation of the effect of time on default. This is often done when, starting from a specified event, the development of the default probability over time is analysed. An example is the question of how the risk of a newly founded company evolves in the first years of its business. Our analysis instead aims at predicting the default rate of a bank in a specific year when the bank has existed for a couple of decades. We therefore introduce time into the model via a baseline hazard rate λ_{0t} and estimate it nonparametrically. λ_{0t} comprises all factors which are not measured by the covariates and which affect the PD of a certain period for all banks with an equal impact. This means that λ_{0t} can be treated like a time effect. We further assume that the covariates only incompletely explain the differences between banks, so that the observations belonging to the same bank will be correlated. The correlation is modelled with the individual effect λ_{i0}. With these assumptions the hazard model can be written as

$$\lambda_{it} = \Phi(S_{it}) \qquad \text{with } S_{it} = \beta_0 + \sum_{j=1}^{m} \beta_j X_{it,j} + \lambda_{0t} + \lambda_{i0}\,. \tag{2}$$

S_{it} is often referred to as the score. The score constitutes an order of the banks according to their riskiness. The link function Φ transforms the score into the PD. Equation (2) illustrates that the discrete-time hazard model is an extension of a binary response model for panel data. The choice of the link function is usually arbitrary, since there are no economic indications on which function to use. In many empirical studies, however, the outcome does not seem to depend much on the specific link function. In the following we will alternatively estimate our model with the logit,

$$\Phi(S_{it}) = \frac{e^{S_{it}}}{1+e^{S_{it}}}\,, \tag{3}$$

the probit

$$\Phi(S_{it}) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{S_{it}} e^{-\frac{x^2}{2}} dx \tag{4}$$

and the complementary log-logistic (cloglog) link function

$$\Phi(\lambda_{it}) = \ln(-\ln(1-\lambda_{it}))\ \ . \tag{5}$$

(3), (4) and (5) are the most widely used link functions for empirical analysis, (3) because of its computational simplicity, (4) because of the popularity of the normal distribution, and (5) because it is the discrete-time version of the proportional Cox-model (see Kalbfleisch, Prentice (1980)). Both (3) and (4) are symmetric and give similar values, though the tails of the logistic distribution are heavier than that of the normal distribution. (5) is asymmetric.

For the time effect λ_{0t} year-dummies can be included in the estimation, thus λ_{0t} is treated as a fixed-effect.[9] Forecasting with a model that contains year-dummies results in a two-step procedure where, in a first step, forecast values for the dummy have to be fixed. Instead, we prefer a one-step estimation in which we minimise the time effect by choosing appropriate variables. Thus, minimising the time effect is part of our specification strategy. The year dummies will be introduced afterwards as a part of the model validation, ie in order to test the null hypothesis that $\lambda_{0t} = 0$.

There are no fixed-effects models for the individual effect λ_{i0}, the only exception being the approach proposed by Chamberlain (1980) for the logit link function. His method, however, requires that the individuals manifest a change of the status in the endogenous variable and

9 We do not consider random-effects models for λ_{0t} because they require the assumption that different λ_{0t} are not temporally correlated. Since λ_{0t} is mainly driven by the macroeconomic development, we consider this assumption unrealistic.

skips all other individuals from the sample. Such a procedure is not feasible for default data as it would restrict the sample to the defaulted banks. We therefore model λ_{i0} as a random effect. For discrete-time hazard models there are two kinds of models.[10] One type is cluster-specific models, which calculate coefficients that have to be interpreted in a manner specific to the institution. A cluster-specific coefficient β_i represents the average of the individual institution's reaction (measured in logit changes) to a change in a covariate. By contrast, population-averaged models measure the logit change of an average institution in reaction to a change in the covariate X_i. Both averages are different because (3), (4) and (5) are nonlinear models. Besides, both methods produce slightly different estimates for the endogenous variable. The cluster-specific model estimates PDs which are conditioned on the individual effect. As a consequence, the output for a specific bank is an interval estimation of the PD. In the population-specific model case, the output PD can be interpreted as an average value for all individuals with the same covariate structure.

Generally, for forecasting purposes both models are meaningful, so we estimate them both. Since we find only negligible differences in the estimated coefficients, in the following we only present the results of the population-averaged model. The population-averaged model can be estimated by GEE following Zeger and Liang (1986). Estimations are carried out with the software package *Stata,* release 8.

10 An overview of the models and their estimators can be found in Pendergast et al (1996) or Hosmer and Lemeshow (2000).

5 Model specification

Economic theory gives only rough ideas for the specification of a rating tool. The main reason is that the relevant theoretical models build on data which are not observable. For example, the most prominent models, which are market-value models (also known as asset value models: see eg Falkenstein et al (2000) for an overview) estimate PDs with the help of market data which are not available for cooperative banks and savings banks. The common feature of most default models is that the default event sets in when the capitalisation (the difference between assets and outside funds) falls below a given threshold, such as zero. We therefore define our task as using balance sheet and macroeconomic information to predict future capitalisation. Our model thus includes variables which measure (1) current capitalisation and variables which forecast returns. As predictors for returns we use (2) current returns and factors that influence future returns. For the latter we include factors that are related to the core activities of savings banks and cooperative banks, namely deposit business, lending business and market transactions. These are variables which capture (3) the credit quality, (4) the market risk, (5) the business cycle, and (6) some macroeconomic prices. Table 2 produces the categories with some examples of variables. Overall we have tested about 100 variables in our analysis.

Table 2: Risk factors and ratios

Risk factor	Examples
Current capitalisation	Equity capital to total assets,
Current return	Cost income ratio, EBIT to equity capital, operating results to equity capital,
Credit quality	Nonperforming loans to total loans, loan loss provisions to total loans, customer loans to total assets, large credits to total credits
Market risk	Stocks to total assets, exchange rate results to total assets, derivative results to operative results
Business cycle indicators	GDP, money, unemployment, Ifo indicators
Macroeconomic prices	Interest rates, stock prices, goods prices, oil price

An alternative categorisation of risk relevant factors for banks is given by the structure of the CAMELS rating. CAMELS is the bank rating system used by the US federal depository regulators (the Federal Reserve, the FDIC, the OCC, the OTS, and the NCUA, see Lopez

(1999) for an overview) mainly for on-site examination and is often taken as a benchmark for other models. The method comprehends separate ratings for capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk. The present model will not be developed with the CAMELS categories, mainly because management quality and liquidity cannot be measured adequately with our data. The management quality of a bank could be assessed with qualitative information (mainly deriving from on-site inspections) which is not available. For liquidity the annual structure of our dataset is inadequate and, in addition, the Principle II liquidity reports are not available for the entire period covered by the study. With our dataset, though, it is possible to generate some proxies for liquidity and management quality (such as the cost income ratio for management quality). We assign these proxies to the other categories.

Following the practice of rating agencies (see eg Falkenstein et. al. (2000)) we separately analyse the variables before creating the model. There are mainly two reasons for this preliminary univariate procedure. First, as table 2 shows, there are often alternative ways to measure the same risk factor. For example, profitability can be measured by net income or EBIT and, without looking at the data, it is controversial which ratio performs best. The second and more important reason is to find out which variables have to be transformed prior to modelling. Variable transformation improves the forecasting performance when the relationship between the variable and the PD is not monotone. As can be seen from equation (2) the PD in the hazard model is a monotone function of the covariates. For many variables monotony is a reasonable assumption and there is no need for a transformation – for example one would expect that a rising equity ratio will, cp, lead to a lower PD. There are, however, some exceptions, the most important case being variables which are affected by volatility. Generally, high volatilities indicate increased riskiness. Due to a lack of long time series, rating systems often incorporate annual changes of ratios instead of volatility, with the consequence that the resulting risk patterns are non-monotone. The growth of the equity ratio, for example, typically manifests a (negative) monotone relationship to PD for low and moderate values. Due to volatility, however, very high values may be associated with growing PDs. In this case the predictive power of the variable in the hazard model can be enhanced when the variable is transformed, so that the resulting variable is a monotone function of PD.

We measure the predictive power of a variable and analyse the monotony assumption with the help of two statistical tools: the area under the receiver operating characteristic curve (*AUR*) and the information value (*IV*)[11]. *AUR* can be calculated by first ordering the data according to the variable of interest and then calculating the percentages of defaults and non-defaults above a certain threshold value of the variable. The receiver operating characteristic (ROC) curve plots the percentages of the defaults against the percentages of the non-defaults for all possible threshold values. As an example, figure 1 shows the ROC curve for the ratio of operating results to equity. The distance of the curve from the diagonal is a graphical measure of the discriminative power of the variable. *AUR* is given by the area under the ROC curve. As the coordinates are normalised to unity, the values of *AUR* range between 1 (maximal positive discriminative power) and 0 (maximal negative discriminative power). If *AUR* equals 0.5 the variable has no discriminative power.

The *AUR* presumes that the monotony assumption is valid. Figure 2 gives an example for the ROC curve when this assumption is violated. The ROC for the annual percentage change in credits to customers is first convex, then concave and finally convex, meaning that a strong reduction and a strong growth of credits are related to high risks, whereas moderate changes are associated with low risks. From this example it becomes evident that the *AUR* does not report the discriminative power of the variable.

[11] The predictive power of a variable can be measured with a variety of other methods such as the accuracy ratio or the Mann-Whitney U-test (1947), most of which are equivalent to *AUR* (see Engelmann et al (2003)), but not to *IV*.

Figure 1 ROC curve for operating results to equity

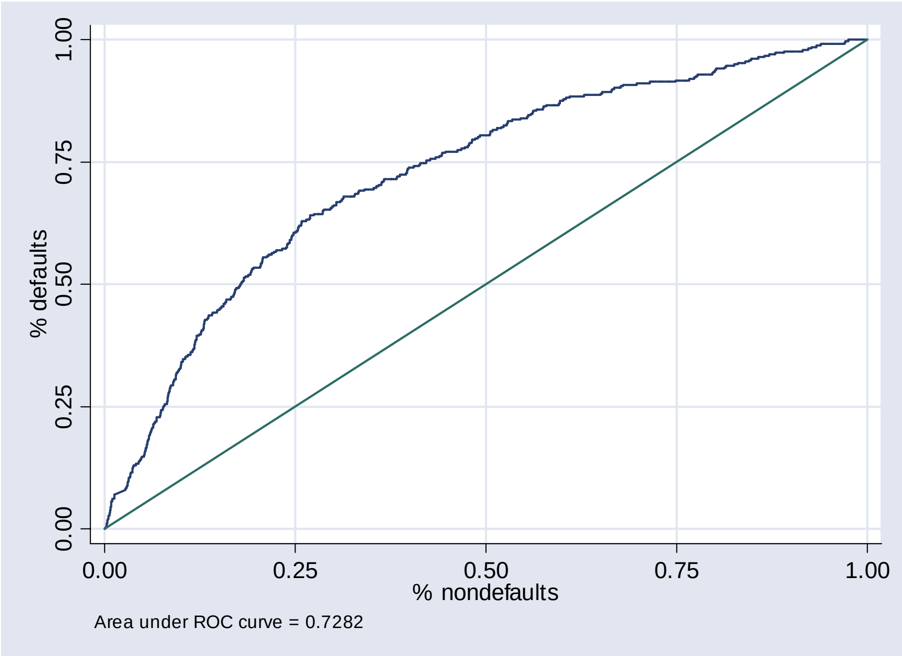
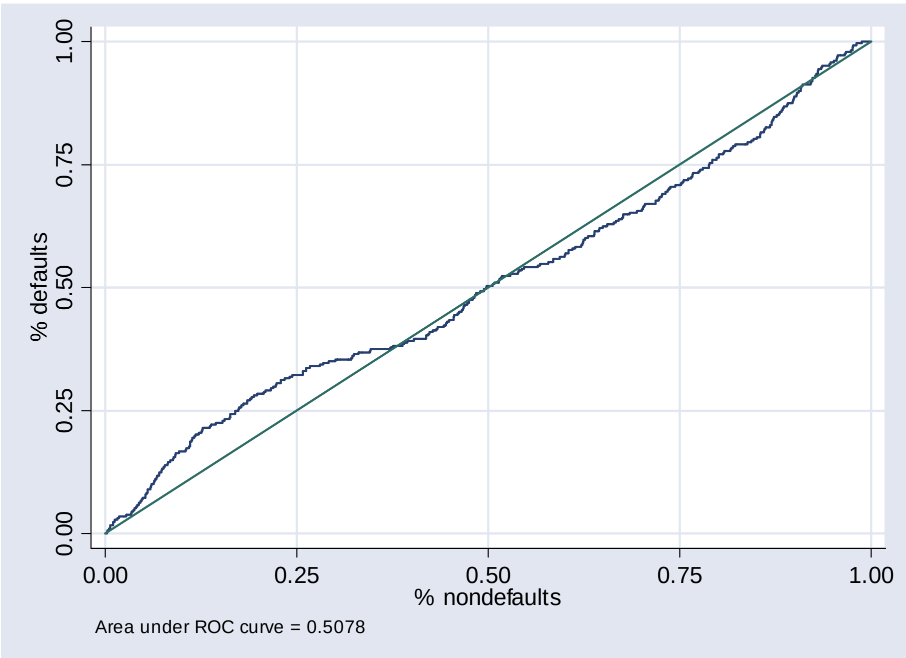


Figure 2 ROC curve for annual percentage change in credits to customers



A measure which is appropriate without the monotony assumption is the information value (*IV*), which can be calculated as

$$IV = \sum_{i=1}^{K} (p_{Ni} - p_{Ai}) \ln\left(\frac{p_{Ni}}{p_{Ai}}\right),$$

where p_{Ai} is the percentage of defaults in class i, p_{Ni} the percentage of nondefaults in class i and K the total number of classes. *IV* measures, in terms of log-odds, how the a priori forecast (default rate of the portfolio) can be improved with the help of the variable. The drawbacks of *IV* are that they require a classification of the data before the calculation[12] and that there is no statistical test related to it. *IV* ranges from zero to infinity. Higher values are associated with a higher discriminative power of the variable.

For each variable, we calculate *IV* and *AUR* and draw the ROC curve. We compare the discriminative power of two variables by testing if the respective *AUR* are equal.[13] In order to check the monotony assumption we inspect the ROC curves and compare the *IV* and *AUR*. If high *IV* is associated with low *AUR* and the ROC is not convex (or concave), an adequate transformation may have a great impact on the performance. We then transform the variables with two alternative methods.

The first transformation entails a classification of the variable. The values of the variables are then replaced by the likelihood ratio of the specific class, where the likelihood ratio is $lr_i = p_{Ai}/p_{Ni}$. This is equivalent to including dummy variables for the classes in the model. The major drawback of this approach is that due to the classification, the information within a class is ignored. Furthermore, there is no theoretically convincing method for choosing the classes.

We therefore also apply an extension of the dummy variable approach that avoids classification and which calculates the likelihood ratio continuously, ie p_{Ai} and p_{Ni} are replaced with the values of the respective density functions.[14] The density functions can be estimated from the sample with kernel estimation. The transformation is optimal in the sense that it maximises the *AUR*; however, the implementation is computationally much more complex than the dummy variable approach. As an example, the appendix reproduces the ROC curves of the annual percentage change in credits to customers for the dummy approach

---

12 The continuous version of IV requires kernel estimation of the conditional density functions and is computationally extensive. The relationship between *IV* and *AUR* is given in Tasche (2002).

13 The test procedure can be found in DeLong, DeLong and Clarke-Pearson (1988).

14 The density functions can be estimated by kernel estimators. For our calculations we use the Gaussian kernel in which the width of the density window is determined by the rule of Silverman (1986).

(figure A1) and for the continuous transformation (figure A2). As expected, both transformations raise the *AUR* (compared to figure 2) and the continuous transformation performs best.

Building on the results of the univariate analysis, we start with the model specification. The model building process is guided by the following ideas. First, the model should contain all categories of variables as shown in table 2. Second, only variables with a significant (univariate and multivariate) impact on the historical defaults were chosen. Third, the model should have a high discriminative power (as measured by *AUR*); and fourth, the annual average PDs should fit the historical default rates. During the specification, estimation was carried out with a sample of the years between 1995 and 2001. The observations of 2002 were used as a hold-out sample of 20% to validate the stability of the model. Then the model finally chosen was reestimated with the whole sample.

6 Results

The coefficients of the population average model are contained in table 3 for alternative link functions. All coefficients have the expected sign and are significantly different from zero.

Table 3: Estimation results for different link functions[15]

	Logit	Probit	Cloglog
Tier 1 capital to risk-weighted assets	-0.109	-0.066	-0.149
	(-2.365)	(-1.973)	(-2.331)
Undisclosed reserves* to balance sheet total	-1.307	-0.879	-1.852
	(-7.647)	(-7.278)	(-7.793)
Undisclosed losses** to Tier 1 capital	0.024	0.022	0.033
	(1.866)	(2.085)	(1.845)
Operating results to Tier 1 capital	-0.006	-0.007	-0.006
	(-2.527)	(-3.359)	(-2.024)
Customer loans to balance sheet total	0.034	0.022	0.049
	(4.040)	(3.567)	(4.285)
Customer loans in t to customer loans in t-1 (transf.)	0.278	0.255	0.382
	(2.167)	(2.469)	(2.210)
Loans with increased risks*** to audited loans	0.018	0.015	0.024
	(4.215)	(4.547)	(4.047)
[Fixed-rate liabilities – fixed-rate assets] to balance	0.039	0.030	0.052
sheet total	(7.114)	(6.995)	(7.129)
Capital market interest rate, annual change	0.287	0.252	0.358
(yield outstanding)	(3.278)	(3.756)	(2.999)
Firm insolvencies to total number of firms	0.866	0.631	1.218
(state level)	(4.203)	(3.801)	(4.386)
Constant	-5.016	-4.524	-7.295
	(-5.885)	(-7.032)	(-6.259)
AUR	0.809	0.814	0.807
R^2	0.592	0.467	0.710

All ratios in per cent, z-values (Wald-test) in brackets.
For reasons of comparability the coefficients of the probit (complementary log-logistic) model are multiplied by $\pi/3^{1/2}$ ($2^{1/2}$).
R^2 refers to a regression of the annual average PDs on the historical default rates.
* Undisclosed reserves pursuant to sections 340f and 340g of the German Commercial Code (HGB).
** Undisclosed losses due to a transfer of securities, stocks or bonds to fixed assets
*** Loans with increased risks and provisioned loans

The current capitalisation is measured with three ratios which comprise tier 1 capital, undisclosed reserves and undisclosed losses due to a transfer of securities, stocks or bonds to fixed assets. The current returns are modelled with operating results, and credit risk with customer loans (level and growth) and loans with increased risks. The growth of customer loans enters the model after it has been transformed with the continuous approach described

15 With the help of the method proposed by Pregibon (1981) outliers were identified and eliminated from the analysis prior to estimation. In our data set, this study ended up excluding three (solvent) banks.

in the previous section.[16] Market risk is measured by the difference between fixed-rate liabilities and fixed-rate assets. Finally, as macroeconomic factors the model includes the growth of the capital market interest rate and regional insolvencies.

The *AUR* of roughly 81% reveals a high discriminative power of all three models. As measured by R^2 the cloglog model seems to explain the annual default rates better than the other models. This result, however, should not be taken too seriously, since the calculation of R^2 is based on 7 observations only. To find out whether the three models perform differently in terms of fit, we compare the empirical default distributions with the theoretical density functions. The plot (see figures A3, A4 and A5 in the appendix, for the calibration we use the empirical mode and variance) reveals a similar fit for all link functions, so the choice of the specific function is arbitrary. For convenience we henceforth only discuss the results from the logit link function.[17]

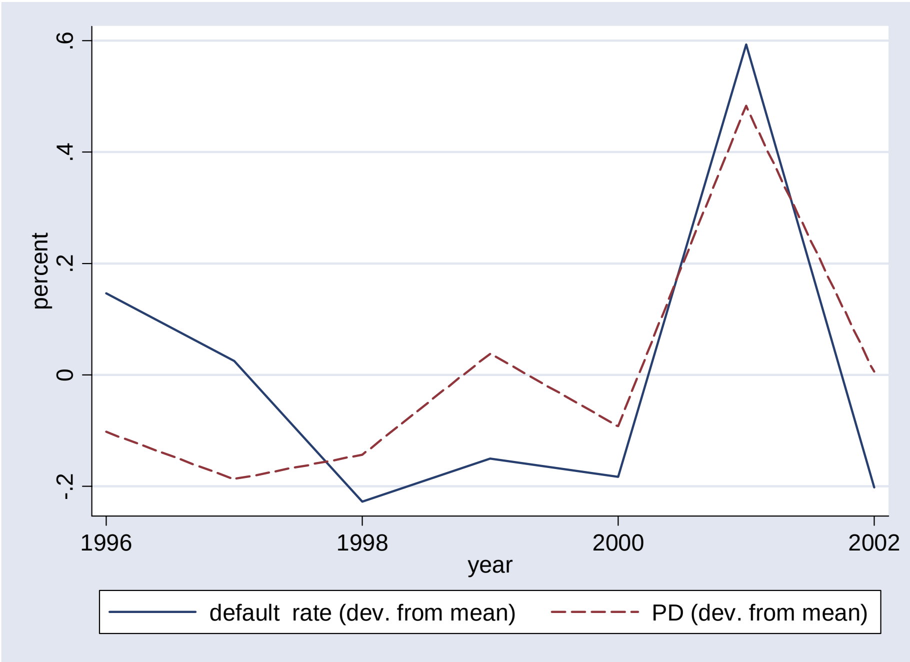
Figure 3 illustrates the fit of the historical default rates. Since the default rates are confidential Bundesbank information, we plot the deviations from the mean. The model is a good predictor for the direction of the development: With only one exception (in 1998), the upward and downward movements of the default rate have been predicted by the model. However, the R^2 presented in table 3 are quite low, indicating that the model only poorly fits the levels of the default rates. Figure 3 reveals that this is particularly true for the years 1996 to 1999. In the following years the levels of the default rates are predicted better. Most notably, the model explains the peak of the year 2001 and also the sharp decline in 2002. We assume that the different performance in both subperiods is due to a structural change in the default time series which probably reflects the severe problems of the German banking system in the last few years (and the efforts to overcome them). This explanation is confirmed by the finding that in the model building process we were able to estimate models with different variables and a similar overall performance. These models all revealed a good fit to the first subperiod, but they were not able to explain the peak in the year 2001. We finally opted for the model in table 3 because we attributed higher importance to the more recent development.

---

16 Note that including the transformed variable considerably complicates a possible implementation of the model. Therefore, for practical purposes, it may be convenient to skip or to replace this variable. In this regard it should be underlined that the model presented in table 3 was designed for academic purposes only.

17 The conclusions that we reach from the following discussion are unaffected by the choice of the link function.

Figure 3 Average PDs and historical default rates (deviations from the average values)



An unbiased estimation of the standard errors in table 3 requires the baseline hazard rate λ_{0t} to be zero. In order to test this hypothesis, dummy variables are introduced separately[18] for the individual years. The results of the Wald tests as reported in table 4 reveal that there are no significant time effects in any of the years.[19]

---

[18] The dummies cannot be introduced simultaneously due to the presence of the interest rate change.

[19] We do not take the significant probit coefficient of the 1996 dummy as evidence for the presence of a time effect, since in the other models the coefficient is insignificant.

Table 4: Test for time effects

	Logit	**Probit**	**Cloglog**
Dummy 1996	0.664	0.392	0.196
	(1.656)	(2.243)	(0.639)
Dummy 1997	0.330	0.140	0.319
	(1.529)	(1.547)	(1.506)
Dummy 1998	-0.058	-0.034	-0.043
	(-0.299)	(-0.420)	(-0.224)
Dummy 1999	-0.176	-0.072	-0.169
	(-0.893)	(-0.895)	(-0.874)
Dummy 2000	-0.072	-0.03	-0.065
	(-0.338)	(-0.342)	(-0.312)
Dummy 2001	0.062	-0.041	0.202
	(0.162)	(-0.250)	(0.577)
Dummy 2002	-0.186	-0.08	-0.161
	(-0.818)	(-0.856)	(-0.724)

Coefficients of the year dummy variables,
z-values (Wald-test) in brackets.

In order to analyse the relationship between macroeconomic and bank-specific factors, we split our model into two separate models: a model which contains only macroeconomic variables and another model which contains only individual variables. Table 5 shows the *AUR* and the R^2 from a regression of the average default probability on the historical default rate for the separate models. The discriminative power (*AUR*) can be attributed almost entirely to the individual bank data. In line with Nuxoll (2003) we find a poor discriminative power of the macroeconomic variables. This is not surprising since they have a smaller variation: their values are equal for each bank of the same year and region. More interestingly, the fit to the average default rate can be attributed almost entirely to the macroeconomic factors. Obviously, bank-specific data mainly determine the relative risk, ie the order of banks by riskiness, whereas macroeconomic information mainly determines the level of risk. Eventually, risk models which rely on financial ratios alone are not able to predict the level of the PD. So, unlike Nuxoll (2003), we conclude that the macroeconomic variables play an important role in predicting defaults.

Table 5: Individual variables versus macroeconomic variables

	Individual variables only			Macroeconomic variables only		
	Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
AUR	0.795	0.799	0.793	0.546	0.546	0.546
R^2	0.021	0.026	0.003	0.646	0.642	0.647

It should be emphasised that the findings do not give evidence of the causal importance of the risk factors, since they are based on a forecasting model and not on a structural model. A forecasting model shows the informative importance of the variables at a given point of time. In our context this means that we can interpret the results in the following way: Without macroeconomic information, only the position of the bank within the whole banking sector (relative risk) can be determined. For estimating the bank's PD, macroeconomic information is necessary. The importance of the macroeconomic information probably depends on the fact that it is more forward-looking than the balance sheet information.

Next, we analyse the informative importance of the individual bank factors. This is done in terms of *AUR*, as the bank-specific variables mainly determine the discriminative power of the model. We calculate the marginal contribution of a single variable to the discriminative power of the model by comparing the overall *AUR* with the *AUR* that results from a model that excludes the variable. Table 6 reports the relative marginal contributions of all bank-specific variables. As expected the variables which are directly linked to the capitalisation (equity, undisclosed reserves and undisclosed losses taken together) have the greatest informative importance. Among these factors, the undisclosed reserves have by far the most predictive power. Obviously, banks which are in severe trouble will start to reduce their undisclosed reserves. Market risk alone has a similar discriminative power as the other risk factors taken together (credit risk and operating results).

Table 6: Relative marginal contributions of the bank-specific variable to *AUR*

	Marg. *AUR*
Tier 1 capital to risk-weighted assets	0.73%
Undisclosed reserves* to balance sheet total	41.20%
Undisclosed losses** to Tier 1 capital	3.23%
Operating results to Tier 1 capital	9.09%
Customer loans to balance sheet total	3.52%
Customer loans in t to customer loans in t-1 (transf.)	2.64%
Loans with increased risks*** to audited loans	11.58%
[Fixed-rate liabilities – fixed-rate assets] to balance sheet total	28.01%

* Undisclosed reserves pursuant to sections 340f and 340g of the German Commercial Code (HGB)
** Undisclosed losses due to a transfer of securities, stocks or bonds to fixed assets
*** Loans with increased latent risks and provisioned loans

7 Validation

Statistical tests for the validation of the model which build on a hold-out sample for 2002 were already performed during the specification. Most notably, the sharp decline of the default rate in the year 2002 was predicted by the model. This section discusses the stability of the model from a qualitative perspective.

The stability of the discriminative power can be analysed by examining annual *AUR* values of the model and the single variables. Table 7 reports the respective values. There is some variation of the performance in the individual years, mainly due to undisclosed losses and the variables which measure credit risk. However, for the whole model the differences are not significant.

Table 7: *AUR* for the hazard model and the single variables per year

Year	Model	Tier 1 capital to risk-weighted assets	Undisclosed reserves** to balance sheet total	Undisclosed losses*** to Tier 1 capital	Operating result to Tier 1 capital	Customer loans to balance sheet total	Customer loans in t to customer loans in t-1 (transf.)	Loans with increased risks**** to audited loans	[Fixed-rate liabilities – fixed-rate assets] to balance sheet total
1996	0.8838	0.2386	0.2210	0.6838	0.2898	0.7491	0.5906	0.7075	0.6161
1997	0.8279	0.3335	0.2993	0.5177	0.2385	0.6041	0.5648	0.7156	0.7669
1998	0.8434	0.2668	0.2228	0.5277	0.1787	0.6867	0.5360	0.6095	0.7657
1999	0.7775	0.3800	0.2628	0.5096	0.2102	0.6566	0.6248	0.5429	0.6358
2000	0.8102	0.3576	0.2037	0.4960	0.3197	0.4718	0.7153	0.6377	0.6621
2001	0.7417	0.4039	0.2881	0.6880	0.3036	0.5335	0.5189	0.6409	0.6164
2002	0.8121	0.3006	0.3215	0.6325	0.3113	0.6489	0.4867	0.7082	0.7265
p-value*	0.1074	0.2079	0.3641	0.0000	0.2034	0.0125	0.0012	0.0280	0.0790

* p-value for H_0: *AUR* for all years are equal.

** Undisclosed reserves pursuant to sections 340f and 340g of the German Commercial Code (HGB)

*** Undisclosed losses due to a transfer of securities, stocks or bonds to fixed assets

**** Loans with increased latent risks and provisioned loans

A second issue which may impair the stability of the model is that one and the same model for savings banks and credit cooperatives may be inadequate. Table 8 presents the univariate and multivariate *AUR* for both subsegments and the results from the test of the hypothesis that both values are equal. For most of the variables there are no significant differences between the subsegments. The variables tier 1 capital and undisclosed losses reveal a better performance for savings banks and the difference is significant on a 5 per cent level. The overall test results in a p-value of 6 per cent, indicating that savings banks can be discriminated slightly better. The result is astonishing, since in the estimation the number of cooperative banks (defaults and nondefaults) is much larger than the number of savings banks. Although cooperative banks dominate the estimation, savings banks have a slightly better performance. We interpret this finding as evidence that the model is appropriate for both banking groups, and that savings banks reveal a higher risk sensitivity[20]. Against that background, using a common model to evaluate savings banks and credit cooperatives is sufficient.

Table 8: Univariate and mulitvariate *AUR* for subsegments

	***AUR* savings banks**	***AUR* Coop. banks**	**p-value for H_0:** *AUR* (savings banks) = *AUR* (coop. banks)
Tier 1 capital to risk weighted assets	0.2417	0.3381	0.0343
Undisclosed reserves* to balance sheet total	0.2187	0.2817	0.1495
Undisclosed losses** to Tier 1 capital	0.6700	0.5659	0.0176
Operating results to Tier 1 capital	0.2719	0.3321	0.2664
Customer loans to balance sheet total	0.6912	0.6005	0.1577
Customer loans in t to customer loans in t-1 (transf.)	0.5399	0.5747	0.4976
Loans with increased risks*** to audited loans	0.6108	0.6533	0.3477
[Fixed-rate liabilities – fixed-rate assets] ÷ balance-sheet total	0.7098	0.6786	0.4825
Capital markets interest rate, annual change (yield outstanding)	0.5179	0.5638	0.4177
Firm insolvencies to total number of firms (state level)	0.5041	0.4445	0.3132
Total	0.8597	0.7989	0.0616

* Undisclosed reserves pursuant to sections 340f and 340g of the German Commercial Code (HGB)
** Undisclosed losses due to a transfer of securities, stocks or bonds to fixed assets
*** Loans with increased latent risks and provisioned loans

20 The p-value of a joint Wald test of the hypothesis of equal coefficients amounts to 5.78%. Here the operating results and the market risk variable have a significant lower coefficient in the savings banks' equation(on the 5 per cent level). The test therefore confirms the result of a higher risk sensitivity of savings banks, attributing it, however, to different variables.

8 Conclusion

German savings banks and cooperative banks constitute an integral part of the German banking system. There is, however, little evidence concerning their default risk. We try to fill this gap in the literature and propose a statistical model which estimates the PDs of both banking groups. Since we adopt a prudential supervisory perspective, default is defined as any event that jeopardises the viability of the bank as a going concern. Our dataset combines default events with balance sheet information, audit reports, and macroeconomic variables. We estimate a discrete-time hazard model.

We find that the relevant factors for the estimation of a bank's PD comprise the general macroeconomic environment and the bank's return, credit risk, market risk and, most importantly for the discrimination, the capitalisation. We further find that using the same model for savings banks and cooperative banks is adequate, although savings banks are more risk sensitive. However, the stability of the results may be impaired by a structural change in the time series of the default rates.

Contrary to former research (see Nuxoll (2003)) we conclude that macroeconomic information is an integral element in forecasting banks' default. There are two main explanations for the differences to the cited study. First, the German regional macroeconomic information is available comparatively early, so that at a given point of time the correlation with the balance sheet information is low. Second, in his analysis Nuxoll has focussed on the discriminative power of the model. However, the discriminative power measures only one aspect of a bank's PD, namely the relative risk, while ignoring the risk level. In our analysis we focus on both the discriminative power and the risk level. Our results show that rating tools which rely solely on financial ratios may not be suited to capture the risk level of a bank. At the same time, adding macroeconomic information to the model greatly improves the forecasting performance.

9 Appendix

Figure A1. ROC curve of the annual percentage change in credit to customers (dummy transformation)

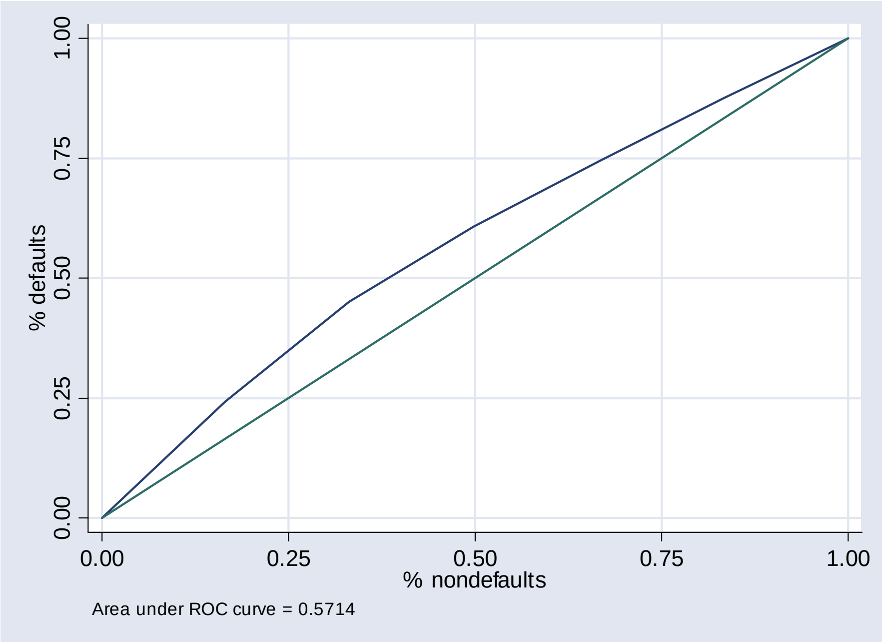


Figure A2. ROC curve of the annual percentage change in credit to customers (continuous transformation)

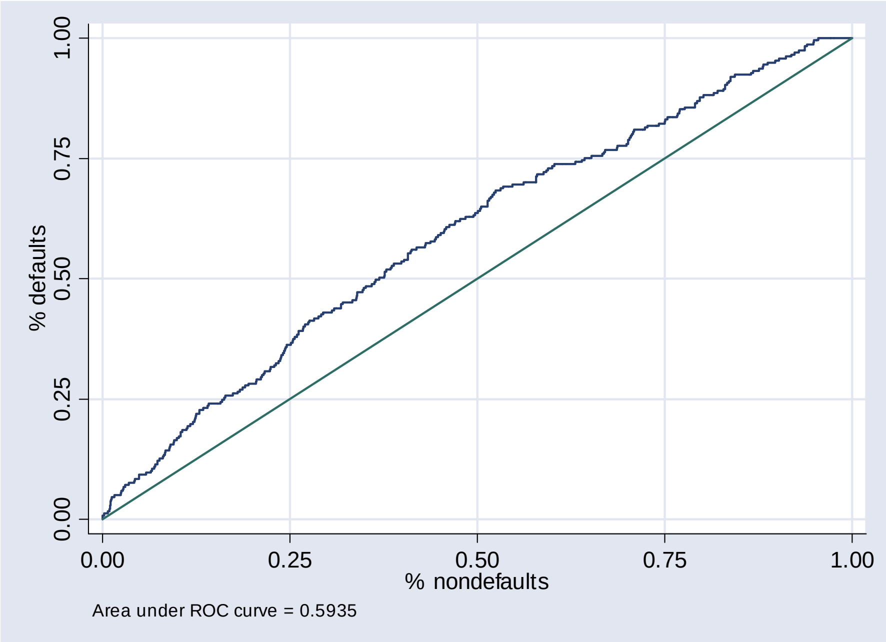


Figure A3. Empirical default distribution and logit distribution

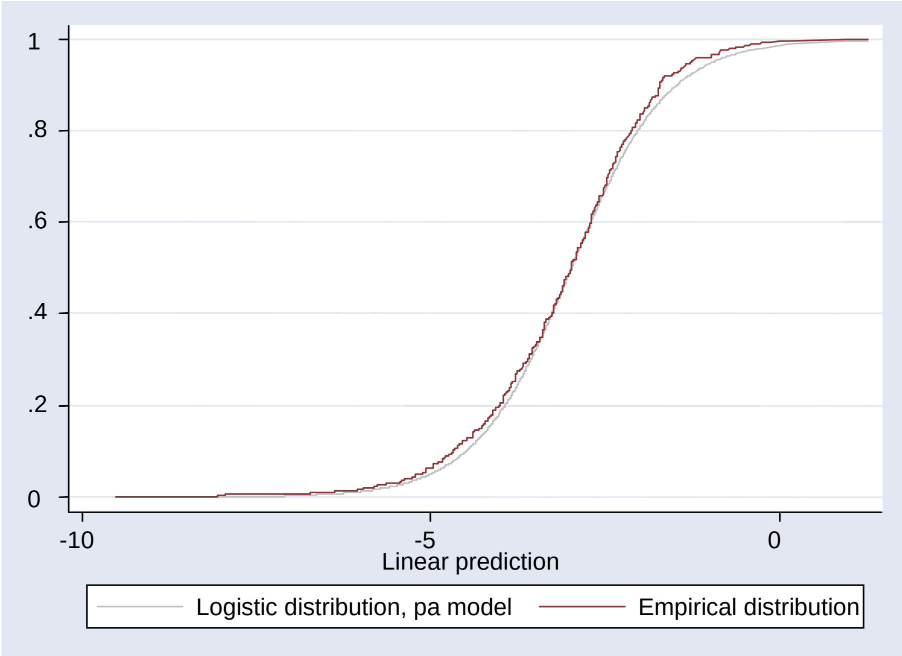


Figure A4. Empirical default distribution and logit distribution

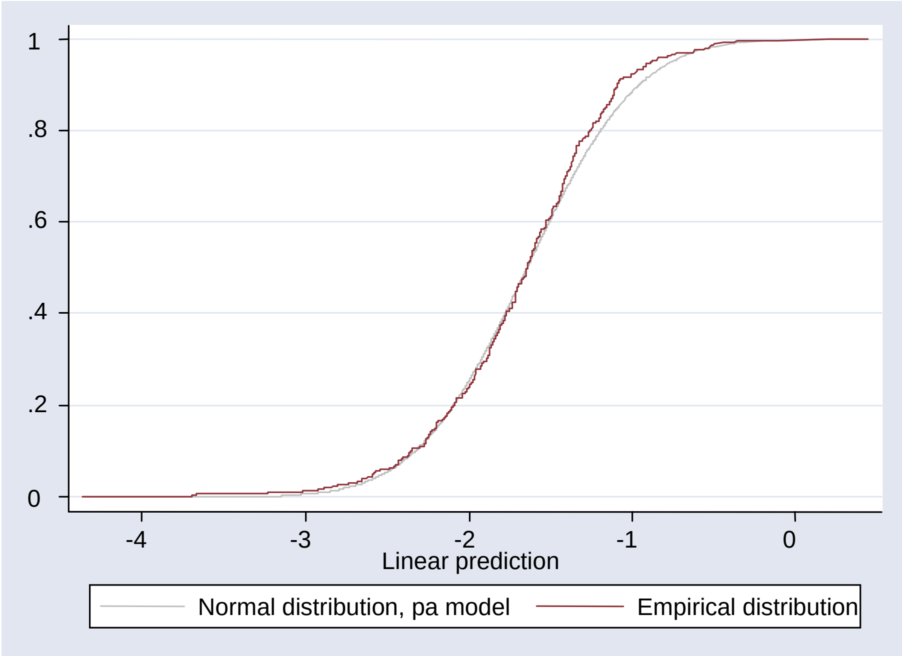
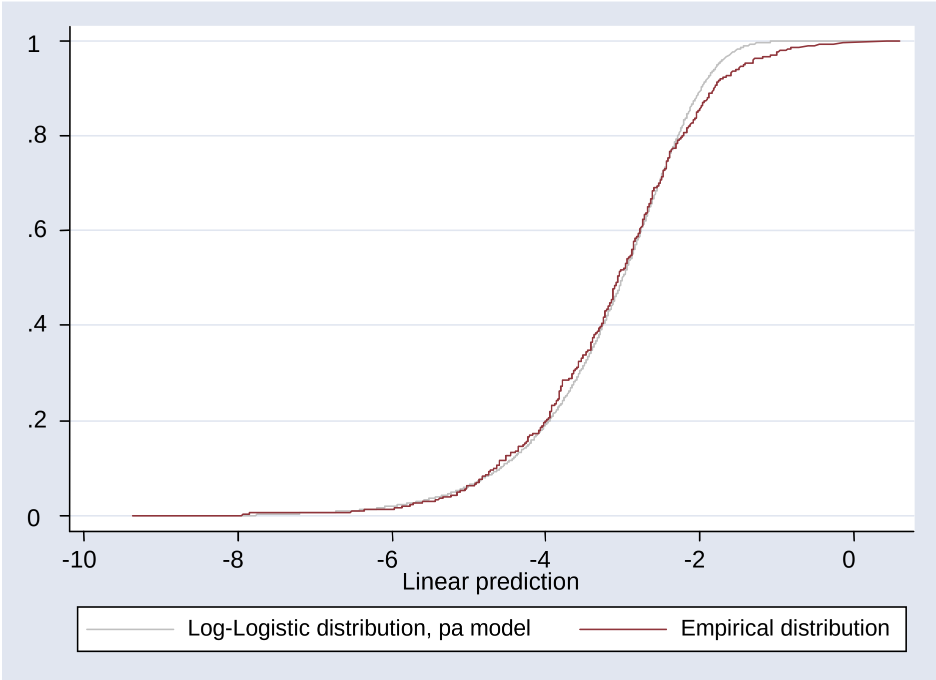


Figure A5. Empirical default distribution and logit distribution



10 References

Altman, E I, 1968, Financial Ratios, discriminant analysis and the prediction of corporate bankruptcy, *The Journal of Finance* 23, 589-609.

Altman, E I, 1977, Predicting performance in the savings and loan association industry, *Journal of Monetary Economics 3*, 443-66.

Beaver, W H, 1968, Alternative accounting measures as predictors of failure, *The Accounting Review* 43, S. 113-122.

Chamberlain, G, 1980, Analysis of covariance with qualitative data, *Review of Economic Studies* 47, 225-238.

Cole, R A, J W Gunther, 1995, Separating the likelihood and timing of bank failure, *Journal of Banking & Finance 19*, 1073-1089.

Claeys, S, G Lanine, K Schoors, 2004, Bank supervision Russian style: rules versus enforcement, *Working Paper*.

Demirgüc-Kunt, A, 1989, Deposit institution failures: A review of the empirical literature, *Federal Reserve Bank of Cleveland Economic Review, Fourth Quarter*, 2-18.

DeLong, E R, D M DeLong, D L Clarke-Pearson, 1988, Comparing the areas under two or more correlated receiver operating curves: a nonparametric approach, *Biometrics 44*, 837-845.

Deutsche Bundesbank, 2004, Banking statistics, *Statistical supplement to the Monthly Report 1, June*.

Engelmann B, E Hayden, D Tasche, 2003, Testing rating accuracy, *Risk 16*, 82-86.

Espahbodi, P, 1991, Identification of problem banks and binary choice models, *Journal of Banking and Finance 15*, 53-71.

Estrella, A, S Park, S Peristiani, 2000, Capital ratios as predictors of bank failure, *Federal Reserve Bank of New York: Economic Policy Review*, July, 33-52.

Falkenstein E. A Boral, L Carty, 2000, RiscCalc private model: Moody's default model for private firms, Moody's Investors Service.

Hamerle, A, T Liebig, H Scheule, 2004, Forecasting credit portfolio risk, *Deutsche Bundesbank: Discussion Paper, Series 2*, No 01/2004.

Henebry, K L, 1996, Do cash flow variables improve the predictive accuracy of a Cox proportional hazards model for bank failure?, *The Quarterly Review of Economics and Finance 36*, 395-409.

Hosmer, D W, S Lemeshow, 2000, Applied logistic regression, Wiley, New York et al, 2nd edition.

IMF, 2003, Germany: Financial System Stability Assessment, www.imf.org

Kalbfleisch, J D, R L Prentice, 1980, The statistical analysis of failure time data, Wiley, New York et al.

Lane, W R, S W Looney, J W Wansley, 1986, An application of the Cox proportional hazards model to bank failure, *Journal of Banking and Finance 10*, 511-531.

Lennox, C, 1999, Identifying failing companies: A reevaluation of the logit, probit and DA approaches, *Journal of Economics and Business 51*, 347-364.

Lo, A W, 1986, Logit versus discriminant analysis: A specification test and application to corporate bankruptcies *Journal of Econometrics 31*, 151-178.

Looney, S W, J W Wansley, and W R Lane, 1989, An examination of misclassifications with bank failure prediction models, *Journal of Economics and Business 41*, 327-336.

Lopez, J A, 1999, Using CAMELS ratings to monitor bank conditions, *Federal Reserve Bank of San Francisco Economic Letter 99-19*, June.

Mann, H and D Whitney, 1947, On a test of whether one of two random variables is stochasitcally larger than the other, *Annals of Mathematical Statistics 18*, 60-70.

Martin, D, 1977, Early warning of bank failure, *Journal of Banking and Finance 1*, 249-76.

Molina, C A, 2002, Predicting bank failures using a hazard model: the Venezuelan banking crisis, *Emerging markets review 2*, 31–50.

Moody's Investors Service, 2003, Banking System Outlook – Germany, www.moodys.com.

Nuxoll, D A, 2003, The contribution of economic data to bank-failure models, *Working Paper*.

Pendergast, J F, S J Gange, M A Newton, M J Lindstrom, M Palta, M R Fisher, 1996, A survey of methods for analyszing clustered binary response data, *International Statistical Review 64*, 89-118.

Pregibon, D, 1981, Logistic regression diagnostics, *Annals of Statistics 9*, 705-724.

Schmidt, R H, M Tyrell, 2004, What constitutes a financial system in general and the German financial system in particular?, in: J P Krahnen, R H Schmidt (eds), The German Financial System, Oxford University Press, 19-67.

Shumway, T, 2001, Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business 74*, 101-124.

Sinkey, J, 1975, A multivariate statistical analysis of the characteristics of problem banks, *Journal of Finance 30*, 21-36.

Silverman, B W, 1986, Density estimation for statistics and data analysis, London, Champman & Hall.

Tasche, D, 2002, Remarks on the monotonicity of default probabilities, *Working paper*, www-m4.mathematik.tu-muenchen.de/m4/pers/tasche.

Zeger, L P and K-Y Liang, 1986, Longitudinal data analysis for discrete and continuous outcomes, *Biometrics 42*, 121-130.

The following Discussion Papers have been published since 2003:

Series 1: Studies of the Economic Research Centre

January	2003	Testing mean-variance efficiency in CAPM with possibly non-gaussian errors: an exact simulation-based approach	Marie-Claude Beaul Jean-Marie Dufour Lynda Khalaf
January	2003	Finite-sample distributions of self-normalized sums	Jeong-Ryeol Kim
January	2003	The stock return-inflation puzzle and the asymmetric causality in stock returns, inflation and real activity	Jeong-Ryeol Kim
February	2003	Multiple equilibrium overnight rates in a dynamic interbank market game	Jens Tapking
February	2003	A comparison of dynamic panel data estimators: Monte Carlo evidence and an application to the investment function	Andreas Behr
March	2003	A Vectorautoregressive Investment Model (VIM) And Monetary Policy Transmission: Panel Evidence From German Firms	Joerg Breitung Robert S. Chirinko Ulf von Kalckreuth
March	2003	The international integration of money markets in the central and east European accession countries: deviations from covered interest parity, capital controls and inefficiencies in the financial sector	Sabine Herrmann Axel Jochem
March	2003	The international integration of foreign exchange markets in the central and east European accession countries: speculative efficiency, transaction costs and exchange rate premiums	Sabine Herrmann Axel Jochem

March	2003	Determinants of German FDI: New Evidence from Micro-Data	Claudia Buch Jörn Kleinert Farid Toubal
March	2003	On the Stability of Different Financial Systems	Falko Fecht
April	2003	Determinants of German Foreign Direct Investment in Latin American and Asian Emerging Markets in the 1990s	Torsten Wezel
June	2003	Active monetary policy, passive fiscal policy and the value of public debt: some further monetarist arithmetic	Leopold von Thadden
June	2003	Bidder Behavior in Repo Auctions without Minimum Bid Rate: Evidence from the Bundesbank	Tobias Linzert Dieter Nautz Jörg Breitung
June	2003	Did the Bundesbank React to Stock Price Movements?	Martin T. Bohl Pierre L. Siklos Thomas Werner
15	2003	Money in a New-Keynesian model estimated with German data	Jana Kremer Giovanni Lombardo Thomas Werner
16	2003	Exact tests and confidence sets for the tail coefficient of α-stable distributions	Jean-Marie Dufour Jeong-Ryeol Kurz-Kim
17	2003	The Forecasting Performance of German Stock Option Densities	B R Craig, E Glatzer, J Keller, M Scheicher
18	2003	How wacky is the DAX? The changing structure of German stock market volatility	Jelena Stapf Thomas Werner

1	2004	Foreign Bank Entry into Emerging Economies: An Empirical Assessment of the Determinants and Risks Predicated on German FDI Data	Torsten Wezel
2	2004	Does Co-Financing by Multilateral Development Banks Increase “Risky” Direct Investment in Emerging Markets? – Evidence for German Banking FDI	Torsten Wezel
3	2004	Policy Instrument Choice and Non-Coordinated Monetary Policy in Interdependent Economies	Giovanni Lombardo Alan Sutherland
4	2004	Inflation Targeting Rules and Welfare in an Asymmetric Currency Area	Giovanni Lombardo
5	2004	FDI versus cross-border financial services: The globalisation of German banks	Claudia M. Buch Alexander Lipponer
6	2004	Clustering or competition? The foreign investment behaviour of German banks	Claudia M. Buch Alexander Lipponer
7	2004	PPP: a Disaggregated View	Christoph Fischer
8	2004	A rental-equivalence index for owner-occupied housing in West Germany 1985 to 1998	Claudia Kurz Johannes Hoffmann
9	2004	The Inventory Cycle of the German Economy	Thomas A. Knetsch
10	2004	Evaluating the German Inventory Cycle Using Data from the Ifo Business Survey	Thomas A. Knetsch
11	2004	Real-time data and business cycle analysis in Germany	Jörg Döpke
12	2004	Business Cycle Transmission from the US to Germany – a Structural Factor Approach	Sandra Eickmeier

13	2004	Consumption Smoothing Across States and Time: International Insurance vs. Foreign Loans	George M. von Furstenberg
14	2004	Real-Time Estimation of the Output Gap in Japan and its Usefulness for Inflation Forecasting and Policymaking	Koichiro Kamada
15	2004	Welfare Implications of the Design of a Currency Union in Case of Member Countries of Different Sizes and Output Persistence	Rainer Frey
16	2004	On the decision to go public: Evidence from privately-held firms	Ekkehart Boehmer Alexander Ljungqvist
17	2004	Who do you trust while bubbles grow and blow? A comparative analysis of the explanatory power of accounting and patent information for the market values of German firms	Fred Ramb Markus Reitzig
18	2004	The Economic Impact of Venture Capital	Astrid Romain, Bruno van Pottelsberghe
19	2004	The Determinants of Venture Capital: Additional Evidence	Astrid Romain, Bruno van Pottelsberghe
20	2004	Financial constraints for investors and the speed of adaption: Are innovators special?	Ulf von Kalckreuth
21	2004	How effective are automatic stabilisers? Theory and results for Germany and other OECD countries	Michael Scharnagl Karl-Heinz Tödter
22	2004	Asset Prices in Taylor Rules: Specification, Estimation, and Policy Implications for the ECB	Pierre L. Siklos Thomas Werner Martin T. Bohl

23	2004	Financial Liberalization and Business Cycles: The Experience of Countries in the Baltics and Central Eastern Europe	Lúcio Vinhas de Souza
24	2004	Towards a Joint Characterization of Monetary Policy and the Dynamics of the Term Structure of Interest Rates	Ralf Fendel
25	2004	How the Bundesbank really conducted monetary policy: An analysis based on real-time data	Christina Gerberding Andreas Worms Franz Seitz
26	2004	Real-time Data for Norway: Challenges for Monetary Policy	T. Bernhardsen, Ø. Eitrheim, A.S. Jore, Ø. Røisland
27	2004	Do Consumer Confidence Indexes Help Forecast Consumer Spending in Real Time?	Dean Croushore
28	2004	The use of real time information in Phillips curve relationships for the euro area	Maritta Paloviita David Mayes
29	2004	The reliability of Canadian output gap estimates	Jean-Philippe Cayen Simon van Norden
30	2004	Forecast quality and simple instrument rules - a real-time data approach	Heinz Glück Stefan P. Schleicher
31	2004	Measurement errors in GDP and forward-looking monetary policy: The Swiss case	Peter Kugler Thomas J. Jordan Carlos Lenz Marcel R. Savioz
32	2004	Estimating Equilibrium Real Interest Rates in Real Time	Todd E. Clark Sharon Kozicki
33	2004	Interest rate reaction functions for the euro area Evidence from panel data analysis	Karsten Ruth

34	2004	The Contribution of Rapid Financial Development to Asymmetric Growth of Manufacturing Industries: Common Claims vs. Evidence for Poland	George M. von Furstenberg
35	2004	Fiscal rules and monetary policy in a dynamic stochastic general equilibrium model	Jana Kremer
36	2004	Inflation and core money growth in the euro area	Manfred J.M. Neumann Claus Greiber
37	2004	Taylor rules for the euro area: the issue of real-time data	Dieter Gerdesmeier Barbara Roffia
38	2004	What do deficits tell us about debt? Empirical evidence on creative accounting with fiscal rules in the EU	Jürgen von Hagen Guntram B. Wolff
39	2004	Optimal lender of last resort policy in different financial systems	Falko Fecht Marcel Tyrell
40	2004	Expected budget deficits and interest rate swap spreads - Evidence for France, Germany and Italy	Kirsten Heppke-Falk Felix Hüfner

Series 2: Banking and Financial Supervision

1	2003	Measuring the Discriminative Power of Rating Systems	B. Engelmann, E. Hayden, D. Tasche
2	2003	Credit Risk Factor Modeling and the Basel II IRB Approach	A. Hamerle, T. Liebig, D. Rösch
1	2004	Forecasting Credit Portfolio Risk	A. Hamerle, T. Liebig, H. Scheule
2	2004	Systematic Risk in Recovery Rates – An Empirical Analysis of US Corporate Credit Exposures	Klaus Düllmann Monika Trapp
3	2004	Does capital regulation matter for bank behaviour? Evidence for German savings banks	Frank Heid Daniel Porath Stéphanie Stolz
4	2004	German bank lending during emerging market crises: A bank level analysis	F. Heid, T. Nestmann, B. Weder di Mauro, N. von Westernhagen
5	2004	How will Basel II affect bank lending to emerging markets? An analysis based on German bank level data	T. Liebig, D. Porath, B. Weder di Mauro, M. Wedow
6	2004	Estimating probabilities of default for German savings banks and credit cooperatives	Daniel Porath