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Slippery slopes of stress: ordered failure events in German banking

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Abstract

Outright bank failures without prior indication of financial instability are very rare. Supervisory authorities monitor banks constantly. Thus, they usually obtain early warning signals that precede ultimate failure and, in fact, banks can be regarded as troubled to varying degrees before outright closure. But to our knowledge virtually all studies that predict bank failures neglect the ordinal nature of bank distress. Exploiting the distress database of the Deutsche Bundesbank we distinguish four different distress events that banks experience. Only the worst entails a bank to exit the market. Weaker orders of distress are, first, compulsory notifications of the authorities about potential problems, second, corrective actions such as warnings and hearings and, third, actions by banking pillar's insurance schemes. Since the four categories of hazard functions are not proportional, we specify a generalized ordered logit model to estimate the respective probabilities of distress simultaneously. Our model estimates each set of probabilities with high accuracy and confirms, first, the necessity to account for different kinds of distress events and, second, the violation of the proportional odds assumption implicit in most limited dependent analyses of bank failure.

Keywords: Bank, failure, distress, generalized ordered logit

JEL: C35, G21, G33, K23, L50

Non-technical summary

Bank insolvencies are different from failures of non-financial firms because they may disrupt trust in the banking system as a whole. This explains why banks are subject to more regulatory scrutiny compared to most other industries. Supervisors therefore monitor banks on an ongoing basis to ensure the financial safety and soundness of individual banks and the system. To this end, they use among other things off-site monitoring systems, which rely mostly on bank-specific financial data reported to the authorities. These so-called hazard rate models predict the probability of default of individual banks on the basis of historical financial and default data.

Obviously, the definition of default is crucial to such analyses. On the one hand, banks are subject to clear-cut failure definitions, such as minimum capital requirements stipulated in laws and regulations. On the other hand, the systemic dangers of bank defaults in conjunction with an ongoing supervision process suggest that regulators, and practitioners, may regard a bank as troubled much earlier than ultimate default in the form of (forced) market exit occurs. We argue in this paper that most bank hazard studies neglect this ordinal nature of what we prefer to define as distress rather than default.

We address the issue by using data on a number of distress events that German universal banks from all three pillars experienced between 1994 and 2004. We categorize these events into four groups of ascending degrees of distress, ranging from early warning information issued by banks to regulators to absorbing events such as closure and restructuring mergers. To account for this pecking order of events, we specify a generalized ordered logit model to predict probabilities of different distress events simultaneously. Our main findings are fourfold.

First, we reject the traditionally employed binomial hazard rate model that pools all distress events without further qualification in favor of an ordered logit model that explicitly allows for an ordered categorical variable of distress.

Second, we further find that not only the level of hazard functions differs significantly across distress events but also the sensitivity of individual components of banks' financial profiles as captured by capitalization, asset quality, management skill, earnings, liquidity (CAMEL) and regional macroeconomic covariates. We report evidence that individual slope coefficients, though not all of them, are significantly different across distress categories.

Third, the most important added value of this model in terms of policy relevant information is the result that some components of financial profiles affect earlier stages of distress stronger. An example of this is managerial skill approximated with stochastic cost frontier efficiency. Other components are particularly important to explain the worst classes of distress, especially total reserve holdings and the share of customer loans.

Fourth, to assess the economic significance of our results we also report marginal effects since coefficient estimates of hazard rate models alone can be misleading. The relevance of using a generalized ordered model is further underpinned by at times substantially different predictions of probabilities of distress of up to 60 basis points relative to a simple ordered logit. In sum, we suggest that future hazard rate studies should attempt to model different degrees of distress more explicitly.

Nichttechnische Zusammenfassung

Bankinsolvenzen unterscheiden sich von Insolvenzen außerhalb des Finanzwesens, da sie das Vertrauen in das Finanzsystem beeinträchtigen können. Außerdem können durch sie schwerwiegende Rückkoppelungen auf die Realwirtschaft ausgelöst werden. Darum werden Banken einer intensiveren Aufsicht unterzogen, als dies für die Mehrzahl anderer Branchen der Fall ist. Die Bankenaufsicht überwacht Institute kontinuierlich, um die Stabilität einzelner Banken und des gesamten Systems sicher zu stellen. Hierzu werden unter anderem statistische Methoden genutzt, um durch die Kombination von historischen Ausfalldaten mit bankspezifischen Kennzahlen die Ausfallwahrscheinlichkeit einer Bank vorherzusagen.

Das Verständnis des Ausfallbegriffs ist hierbei von offensichtlicher Bedeutung. Einerseits sind Bankenausfälle in Gesetzen und Richtlinien eindeutig geregelt, zum Beispiel durch Mindesteigenkapitalanforderungen. Andererseits legen die systemischen Gefahren von Bankinsolvenzen in Verbindung mit der kontinuierlichen Bankenaufsicht nahe, dass Aufsichtsbehörden und Praktiker eine Bank als problematisch einstufen können, deutlich bevor diese faktisch insolvent wird und aus dem Markt ausscheiden muss. Wir schlagen in dieser Studie ein Modell vor, welches die ordinale Sortierung problematischer Ereignisse (anstatt von "Ausfällen") berücksichtigt.

Hierzu nutzen wir einen Katalog unterschiedlicher Ereignisse, welche sich bei deutschen Universalbanken aller drei Säulen zwischen 1994 und 2004 ereignet haben. Wir kategorisieren vier Gruppen problematischer Ereignisse, welche in ihrer Schwere von Frühwarnsignalen in Form von Mitteilungen der regulierenden Behörden einerseits, bis hin zu absorbierenden Ereignissen wie Fusionen andererseits reichen. Empirisch berücksichtigen wir diese Ordnung nach Schwere der Ereignisse mit Hilfe eines *ordered logit* Modells. Unsere Hauptergebnisse sind wie folgt:

Erstens lehnen wir die Hypothese eines binomialen Hazardratenmodells ab. Statt dessen unterstützen unsere empirischen Ergebnisse die Wahl eines ordered logit Modells, welches die aufsteigende Schwere von Ereignissen explizit zulässt.

Zweitens zeigen wir, dass nicht nur die Achsenabschnitte je Problemkategorie variieren, sondern auch einige, wenngleich nicht alle, Steigungsparameter der Hazardfunktionen je Kategorie signifikant unterschiedlich sind. Je nach Schwere des Ereignisses reagieren somit die jeweiligen Eintrittswahrscheinlichkeiten der einzelnen Problemkategorien unterschiedlich sensitiv auf eine identische Änderung individueller Komponenten des Finanzprofils einer Bank.

Das dritte Ergebnis weist auf die unterschiedliche Bedeutung einzelner Finanzprofilkomponenten für unterschiedliche Problemereignisse hin und könnte damit von besonderer praktischer Relevanz sein. Wir zeigen, dass schwache Ereignisse insbesondere von der Qualität des Managements (gemessen mittels stochastischer Kosteneffizienz) abhängen. Letztere ist jedoch von nachrangiger Bedeutung für schwerere Ereignisse, welche vielmehr von der Reservehaltung und der Kreditqualität determiniert werden.

Viertens berechnen wir marginale Effekte, um die ökonomische Signifikanz unserer Ergebnisse aufzuzeigen. Unsere Spezifikation eines flexiberen Modells wird zudem dadurch bestätigt, dass im Vergleich zu einem restriktiveren Hazardmodell geschätzte Eintrittswahrscheinlichkeiten um bis zu 60 Basispunkte abweichen können. Insgesamt schlagen wir daher vor, in Zukunft den Versuch zu unternehmen, unterschiedliche Problemereignisse explizit zu modellieren.

Contents

Slippery slopes of stress: ordered failure events in German banking[1]

1 Introduction

Monitoring and promoting the stability and soundness of banking systems is one of the major concerns of international policy makers (see for example the Bank for International Settlements (1999; 2003; 2004), the European Central Bank (2005), the International Monetary Fund (Caprio and Klingebiel, 1996; Dell'Ariccia et al., 2005), the Bank of England (Hoggarth et al., 2004), Deutsche Bundesbank (2005) or the Federal Deposit Insurance Scheme (King et al., 2005)). Beginning with the work of Sinkey (1975), Martin (1977) and Altman (1977) on failures of U.S. banks numerous studies therefore seek to predict probabilities of bank default on the basis of financial data.

These and most subsequent studies, such as Porath (2006), use a hazard model that transforms a set of (mostly) bank-specific covariates observed in year t into the probability of default (PD) with an appropriate link function (such as logit or probit). The PD can be estimated with historical data of the covariates x observed in t and the actual state of default in $t+1$. The individual bank PD in a given year PD_{it} is the probability that bank i defaults within one year.

The definition of bank defaults usually follows the conventions applied by regulatory authorities. For example, most U.S. studies define failure either as closure by regulators due to capital ratios falling below 2 percent or a merger assisted by the FDIC (Cole and Gunther, 1995).[2] Clearly, the definition of bank default is crucial since this is precisely the event of interest to policy makers and practitioners. In contrast to non-financial firms, however, this definition is non-trivial since outright bankruptcies used in the latter type of studies are rare in banking. This is because individual bank failures may disrupt trust in the system as a whole, which explains why the industry is characterized by more intense regulation seeking to prevent individual and systemic crises (Benink and Benston, 2005).

Failure definitions are usually less obvious than they appear to be in the case of U.S. banking. For example, in our data no single bank violated regulatory minimum capital requirements. But the scenario that no German bank was distressed since 1993 seems unlikely. This finding more likely indicates that bank distress is signalled already before outright failure events occur, which in turn ignite measures

[1]Thomas.Kick@bundesbank.de (T. Kick) and m.koetter@rug.nl (M. Koetter). We are grateful for comments received at the Stress Testing Workshop hosted by the Deutsche Bundesbank and the NAKE conference hosted by the Dutch Central Bank. In particular, we thank Geraldo Cerqueiro, Hans Degryse and Elmer Sterken for their feedback. We are also grateful to Frank Heid for stimulating discussions and Ferre de Graeve, Rudi Vander Vennet and Volker Zeller for most valuable comments. We thank the Deutsche Bundesbank for providing us with data. This paper is part of a research project funded by the "Stiftung Geld und Währung". The paper represents the authors' personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank. All remaining errors are of course our own.

[2]FDIC: Federal Deposit Insurance Scheme.

taken by market participants and/or regulators to forestall disrupting bank closures. Therefore, observed failure events are usually unavailable for most banking markets to the public. Many (non-U.S.) studies therefore resort to alternative definitions. For example, Dabos and Escudero (2004) analyze Argentinean bank failures defined as those that closed during the two year period following the Tequila crisis ignited by the devaluation of the Mexican Peso on December 20^{th}, 1994. This definition is problematic if some banks are taken over by competitors for entirely different reasons than distress resolution, for example the existence of just favorable acquisition conditions. In a study of German bank failures, Elsas (2004) defines events on the basis of persistent membership in the worst annual deciles of the banking population's loan-loss provision share distribution. This categorization is also troublesome if probabilities of default are subsequently estimated with, among other factors, credit quality for reasons of endogeneity.

These obstacles associated with the definition of bank distress are, however, not confined to bank failure studies outside the U.S. as noted by Oshinsky and Olin (2006). According to them, official failure is only one of many options how markets and regulators deal with troubled banks in general. They report for a sample of U.S. banks that troubled banking firms merged, received capital assistances, recovered or merely continued to exist as a troubled bank. In fact, only five percent of all troubled banks in their sample were eventually closed. Other studies by Wheelock and Wilson (2000), Worthington (2002), DeYoung (2003) and Koetter et al. (2006) that allow for multiple distress and/or exit events confirm that troubled banks do not face a dichotomous destiny limited to survival or failure only.

But to our knowledge neither of these studies account for the pecking order that we hypothesize to exist between different states of distress when predicting bank PD's. Only one study by DeYoung et al. (2001) on U.S. bank ratings is methodologically related to ours. The authors compare supervisory CAMEL bank ratings to the market's evaluation inherent in subordinated debt risk spreads of the parent banking firm.[3] For the case of U.S. banks, CAMEL ratings result from both off-site financial information as well as expert evaluations formed during on-site inspections (King et al., 2005). Hence, the authors hypothesize that confidential CAMEL supervisory ratings contain additional information compared to evaluations of other market monitors, such as rating agencies. To extract the confidential, additional information inherent in CAMEL ratings they use an ordered logit model to regress publicly available financial information on these ratings.[4] DeYoung et al. (2001) argue that the residuals from this regression capture the private information available to regulators due to on-site inspections. Subsequently, they analyze if and when an option-adjusted risk premium on subordinated debt is adjusted for these added information. They find that on-site inspections yield indeed additional information that is at times priced only slowly into markets risk premia.

We argue that this and previous studies on bank failure suffer from three problems that we seek to address in our study. First, any (CAMEL) rating results from assigning (an) estimated (distribution of) probabilities of default to rating classes. These classes are by definition ordinally scaled. However, whether estimated probabilities account for the ordinal nature of the observed event of interest depends on

[3]CAMEL: **C**apitalization, **A**sset Quality, **M**anagement, **E**arnings and **L**iquidity.

[4]CAMEL ratings range from 1 (least severe) to 5 (most severe).

the previously discussed definition of distress in the first place. While U.S. supervisors' CAMEL ratings may include valuable private information, it subsequently represents an addition to explanatory variables in a dichotomous failure model instead of a more differentiated definition of bank distress events on the left-hand side (King et al., 2005). Second, the approach by DeYoung et al. (2001) to regress public financial information on confidential CAMEL ratings is infeasible for most European banking markets since, in contrast to the U.S., the vast majority of banking firms are not traded publicly. Hence, most banks do not report financial statements, let alone additional qualitative information, for example on asset quality, to the public. Third, if distressed events are ordered events, it should be tested if not only intercepts of estimated hazard functions capture increasing degrees of distress but also if individual slope coefficients differ across distress categories. We seek to fill these gaps with our study on German universal bank distress using a generalized ordered logit model.

We use a unique data set collected by the German central bank on a variety of distress events experienced by universal banks between 1994 and 2004. We order these records according to severity into four categories. The first and weakest category I of distress includes compulsory notifications of regulatory authorities as stipulated in the German Banking Act (*"Kreditwesengesetz, KWG"*).[5] The second distress category II comprises official warnings or disagreements of the regulatory authority, the Federal Financial Supervisory Authority (*"Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin"*). The next distress category III are interventions by the respective banking sector's insurance scheme in the form of capital injections as well as binding measures issued by the BaFin, for example restrictions to lending and deposit taking. We argue that in contrast to the former category, these distress events represent an active intrusion into the management of the banking firm that curbs perfectly free market competition. Finally, category IV comprises distress events that entail the exit of a bank from the market, either through closure ignited by the regulator in charge, the BaFin, or through mergers classified as restructuring mergers. The latter are usually ignited by the respective banking pillars' head associations (the German Savings and Giro Association, *"Deutscher Sparkassen und Giroverband, DSGV"* and the Federal Association of Cooperative Banks, *"Bundesverband der Deutschen Volksbanken und Raiffeisenbanken, BVR"*).

We hypothesize that these four categories of events reflect fundamentally different kinds of distress that require more explicit modeling. While the particular choice of distress events here is in line with the institutional and regulatory regime prevailing in German banking, we argue that the logic of different degrees of distress applies to other banking systems, too: some banks catch attention by regulators for suboptimal performance while others need to be closed or forced out of the market through mergers to avoid jeopardy of the system's stability.

Our results confirm that bank distress events can be modeled by the ordered logit approach. Using both bank-specific and regional macroeconomic covariates, we find that distress is increasingly less likely for well-capitalized, profitable banks and more likely for banks with low levels of total reserves and high shares of poor quality loans. These findings are qualitatively well in line with previous studies on bank distress (Wheelock and Wilson, 2000; Porath, 2006; Koetter et al., 2006). However, our

[5] We introduce the institutional setting of German banking supervision in section 2.

model improves on previous studies in three important respects. First, we find that the proportional odds assumption implicit in traditional limited dependent analyses of the banking industry is violated. Put differently, the sensitivity of the respective probabilities for a change in individual covariates is not identical for different kinds of ordered distress events. For example, an increase in the capitalization ratio has a strong reducing effect on category I and II distress events. However, it is of minor relevance to reduce the likelihood of more severe distress events. Second, our model includes not only small savings and cooperative banks but also large banks from all three banking sectors, commercial, savings and cooperatives.[6] Since especially large banks did not experience absorbing failure events, such as closure or forced takeovers, this important sector of the industry has not been analyzed previously. Third, compared to most other bank failure studies, the accuracy of our model to correctly classify (ordered) failures from non-failures is high. This supports our argument to model different degrees of bank hazards more explicitly.

The remainder of this paper is organized as follows. In section 2 we briefly introduce the institutional supervision setting in German banking. In section 3 we discuss next our distress data, the choice and hypotheses regarding explanatory covariates and present also our empirical model. We present major findings subsequently in section 4 and conclude in section 5.

2 Institutional background

Despite ongoing harmonization since the late 1980's the supervisory landscape in European banking is still heterogenous (Carletti et al., 2006). In most countries a single institution is responsible for banking supervision. This is usually the central bank, which in turn is typically accountable to the Ministry of Finance (Barth et al., 2001). In Germany, two institutions supervise banks. The first is the Federal Financial Supervisory Authority (*"Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin"*) and the second is the German central bank, the Deutsche Bundesbank (BBK).

The BaFin is responsible for all sovereign measures. This includes licensing and potentially closing individual institutions, but also issuing general instructions for carrying out banking business, providing financial services and limiting risks. The Bundesbank is assigned most of the operational tasks in banking supervision. These are the issuing of principles and regulations, the process of ongoing supervision (except individual regulatory measures vis-à-vis institutions), prudential audits, international cooperation/coordination in the prudential field, and crisis management. Especially through its ongoing monitoring activities using its network of branches (*"Hauptverwaltungen"*) across Germany, the Bundesbank collaborates

[6] This group includes the big five commercial banks, central cooperative and central savings banks (*"Landesbanken"*) since they operate on a(n) (inter)national basis and share more characteristics across banking sectors compared to the profile of their respective pillar's smaller competitors (Koetter et al., 2006).

with the BaFin in the field of banking supervision (Deutsche Bundesbank and BaFin, 2002).

As a general rule of the Banking Act, the supervisory agencies should minimize direct interference in the individual operations of financial institutions. An explicit aim of the Banking Act is to leave the responsibility for business operations to managers of the financial institutions. In general, banking supervision restricts the activities of the financial institutions primarily by qualitative and quantitative general provisions and requires banks to open their books to the supervisory authorities. However, the BaFin may also decide to intervene more directly if deemed necessary.

On a regular and annual basis, all banks report balance sheets, profit and loss accounts as well as compulsory audit reports compiled by independent auditors to the Bundesbank. In addition, Bundesbank auditors conduct less frequent on-site examinations of banks. Violations of the Banking Act are forwarded by the Bundesbank to the BaFin, which after examination formulates next steps to intensify supervision or issue sanctions.[7]

The BaFin has a range of measures to intervene when a bank fails to meet regulatory requirements or poses a threat to stability. Most of these measures are of a warning nature, for example hearings of the banking board, admonishments of executives or sending formal letters of warning. The BaFin can also issue more strict interventions, such as prohibiting to grant new credit or ultimately to ignite closure of the bank.[8] Before such measures are applied, the institution is typically given time to correct the deficiency. This gradual approach of intensified supervision is exactly representative of ordered distress events banks can experience.

With or without having received warnings by the BaFin, banks may experience further distress in the sense of receiving assistance by their respective sector's head organization. The three sectors, also known as banking pillars (Koetter et al., 2006) are commercial, savings and cooperative banks, all of which maintain self-organized insurance funds. Akin to capital injections to local U.S. banks through their bank holding company (Oshinsky and Olin, 2006), the scheme of private commercial banks (Deposit Guarantee Fund of the Federal Association of German Banks, *"Einlagen-sicherungsfonds des Bundesverbandes deutscher Banken"*), the head association of savings banks (German Savings and Giro Association, *"Deutscher Sparkassen und Giroverband, DSGV"*) and cooperative banks (Federal Association of Cooperative Banks, *"Bundesverband der Deutschen Volksbanken und Raiffeisenbanken, BVR"*) may support troubled members by means of capital injections.[9] In addition, failure to comply with earlier warnings issued by the regulator may lead to increasingly binding sanctions such as for example the prohibition of profit distributions.

In sum, banking supervision in Germany involves a tight network of regulators from both the Bundesbank and the BaFin as well as the close involvement of the respective banking sector's head organizations and auditors. Bank distress occurs

[7] Note, however, that the banking act stipulates that the BaFin shall base its regulatory measures on the Deutsche Bundesbank's audit findings and appraisals.

[8] Technically, it is the bank itself that has to file bankruptcy.

[9] Note that the scheme of private commercial banks entails deposit insurance while the latter two involve a further reaching general insurance against bank insolvency (*"Institutssicherung"*).

in multiple shades, ranging from early warning signals igniting formal indication to authorities required by law to forced closure by the BaFin. We discuss next our empirical model to capture the order of these events, distress definitions and our choice of explanatory variables.

3 Methodology and data

Distress categories We collect data from records gathered by the Bundesbank about distress events among universal German banks of all three sectors between 1994 and 2004. As stressed in section 2 it should be noted that these records do not represent interventions of the Bundesbank itself. Rather, the data represent a comprehensive collection of notifications from banks as required by law, own records of the Bundesbank regarding early warning signals on the basis of reported balance sheet, profit and loss account as well as audit report data, supportive actions taken by the sectors' head associations and finally measures taken by the BaFin.

In addition to the first group of non-distressed bank year observations, we categorize four groups of distressed events of increasing severity. The respective distributions over time are shown in table 1. The first group of weakest events comprise three incidents. First, a decline of annual operational profits of more than 25 percent. Second, a notification by banks of losses amounting to 25 percent of liable capital. Third, notifications by banks about events that may jeopardize the existence of the bank as a going concern. The latter two incidents are compulsory notifications as stipulated in §29(3) and §24(1), respectively, of the Banking Act. None of these events implies per se a change of the bank as a going concern. Distress events of this category reflect instead the earliest signs of problems and are of of an indicative nature.

The second category of distressed events captures measures taken by the BaFin representing official warnings or disagreement. Hence, none of these measures implied an active intrusion into the ongoing business operations of the bank. In total, our data distinguishes 59 different kinds of measures. We allocate 26 to more severe categories of events since they include the explicit prohibition of certain activities or even closure of the bank. From the remaining 24 events around 80% involve one of the four following measures: admonishment hearings, disapproval, warnings to CEO, and serious letters.[10]

We regard these events as the second worst distress category since they reflect corrective actions regarding management and business processes by means of warning the bank officially. Note that we do not investigate here the appropriateness of any such actions. Instead, we merely observe that a considerable number of banks were subjected to such corrective actions. However, none of these implied an outright market distortion, such as a subsidy, but represent early warnings of official disapproval.

[10]We neglect nine kinds of events either due to missing data or not representing distress, for example the sending of regular letters.

Table 1: Distribution of distress events 1995 to 2004

Year	**Distress category**					**Total**
	0	*I*	*II*	*III*	*IV*	
1995	2,988	4	11	23	19	3,045
1996	2,965	4	12	37	22	3,040
1997	2,894	2	21	26	49	2,992
1998	2,773	4	39	36	53	2,905
1999	2,618	6	63	23	55	2,765
2000	2,447	3	54	24	43	2,571
2001	2,188	17	67	24	42	2,338
2002	1,993	24	67	17	32	2,133
2003	1,855	14	66	20	22	1,977
2004	1,784	8	45	15	6	1,858
Total	24,505	86	445	245	343	25,624

In contrast, our next distress category captures those incidents where the bank either received support from their respective head association in the form of capital preservation measures or was limited in it's scope of operations by the BaFin. We argue that the former kind of intervention is a more drastic class of distress since it suggests that compliance with legal capitalization requirements was sufficiently endangered as to actively subsidize the bank. In addition, we classify the following measures by the BaFin as category III distress events: orders to restructure operations, restrictions to lending, deposit taking, equity withdrawal or profit distribution and the dismissal of the Chief Operating Officer. These interventions represent active intrusions into the ongoing management of the bank and thus represent severe distress according to our definition.

Our last distress category includes all those events which imply the bank to cease as a going concern. This class comprises two events. The first are takeovers classified by the Bundesbank as restructuring mergers.[11] These are usually ignited by head organizations if alternative measures seem futile or if previous measures did not improve the bank's situation. The second class are enforced closures of banks initiated by the BaFin, which are extremely rare. This ultimate level of distressed events are absorbing incidents that cause the bank to terminate it's operations and exit the market.

Specification We thus want to estimate the probability P that the ordinal distress indicator Y of bank i takes on the value $j = 1, .., M$, where M is the number of event classes. To this end, Greene (2003) writes an ordered logit as

[11]Note that these mergers are not ordered but merely classified as such by the Bundesbank.

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

where X_i is a vector of explanatory variables for bank i and α and β are parameters to estimate. Note that this model nests the more commonly used logistic regression model if $M = 2$ in equation (1). Moreover, if our categorization of distressed events indeed reflects increasing severity, we expect the j hazard functions intercepts α_j to exhibit increasingly large negative values (Greene, 2003).

An important assumption in this model that is usually only briefly mentioned is the so-called parallel odds assumption. Note that in equation (1) only the constant cut-off parameters α_j differ across distress categories. In turn, the slope parameters of the link function are assumed to be identical. Put differently, the effect of a change in X_i, for example profitability or asset quality, is expected to have the same effect on the probabilities of weak distress incidents and forced closures, respectively.[12] Only few studies mention this assumption explicitly (Clogg and Shihadeh, 1994), which in our case seems to be particularly inappropriate. Therefore, we follow the suggestion of Williams (2006) and specify instead a generalized ordered logit model (GOLT). This model allows not only for intercepts specific to different categories j, but also for alternative slope parameters:

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

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

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

Hence, the generalized ordered logit model is equivalent to a series of simple logistic regressions that lump the ordered dependent variables' categories into one. In our case with $M = 5$, for example, category $j = 1$ is compared with categories $j = 2, .., 4$ as a reference group. Likewise, for $j = 3$ the comparison is between groups 1 through 3 relative to groups 4 and 5.[13] We test below whether the proportional odds assumptions is (partly) violated and provide also a comparison of resulting PD distributions from the most commonly employed logistic regression in comparison

[12] Clearly, the logistic regression model is even more restrictive since also the α's are assumed to be identical.

[13] Alternatively, one may model the events as a multinomial logit model, which also allows for group-specific slope coefficients (see for example Koetter et al. (2006) and Focarelli et al. (2002)). Two drawbacks of this model are, first, the neglect of the ordinal nature of events and, second, a larger number of parameters to estimate (Williams, 2006).

to the (generalized) ordered logit models. Before turning to our results, let us turn briefly to our selection procedure for the vector of explanatory covariates.

Explanatory variables To estimate respective probabilities of distress, we follow the financial economics literature and select financial covariates resembling the CAMEL profile of the bank as well as macroeconomic covariates. Our selection procedure follows the suggestion of Hosmer and Lemshow (2000) and unfolds in short as follows. First, we generate a long list of potential CAMEL candidates of around 150 covariates. Second, we shortlist around 50 covariates on the basis of univariate explanatory power for both category-specific and pooled failure events such that each CAMEL category is covered. Next, we select a further reduced vector of covariates with stepwise logistic regression. Finally, we select the final vector of covariates on the basis of statistical and economic significance. This procedure leaves us with nine covariates for which we depict mean values per event category in table 2.[14]

Table 2: Mean values for CAMEL covariates 1995-2004

		Distress category					
Variable		*0*	*I*	*II*	*III*	*IV*	**Total**
Equity ratio	c_1	8.35	9.93	7.71	7.21	8.08	8.33
Total reserves	c_2	0.96	0.44	0.73	0.36	0.44	0.94
Risky loans	a_1	10.93	13.69	13.03	15.12	13.85	11.06
Customer loans	a_2	58.54	55.63	61.89	58.78	60.81	58.62
OBS activities	a_3	3.09	3.04	3.05	4.00	3.61	3.10
Cost efficiency	m_1	83.08	74.42	80.49	79.08	80.06	82.93
RoE	e_1	15.35	0.48	7.24	1.42	3.01	14.86
Liquidity	l_1	6.56	8.77	7.68	7.72	7.54	6.61
Insolvencies	INS	0.86	1.24	1.04	1.12	0.88	0.87

Notes: All variables measured in percent. c_1: Core capital to risk-weighted assets, reserves to total assets, a_1: Provisioned loans and loans with increased risks to audited loans, a_2: Customer loans to total assets, a_3: Off balance sheet activities to total assets, e_1: Operating results to balance sheet total, m_1: Cost efficiency, l_1: Net interbank assets and cash to total assets, INS: Corporate insolvency ratio per state ('Bundesland').

We expect that better capitalized banks are in general less prone to experience distressed events. We therefore specify, first, the equity ratio and, second, the total reserve ratio. Especially the latter include in line with German accounting rules

[14]As in Koetter et al. (2006), we choose a lag of one period based on univariate explanatory power. Qualitatively, results for lags of up to three years are not affected.

undisclosed reserves (*"Stille Reserven"*) and we expect negative coefficients for both variables. Next, we specify three variables to capture asset quality: the share of customer loans, the share of risky loans and the share of off-balance sheet activities. Compared to interbank or government loans, a larger share of customer loans exposes the bank to higher credit risk (Porath, 2006). Clearly, a larger share of risky loans should also increase *cet. par.* the likelihood of a bank to fail. Finally, off-balance sheet activities comprise primarily credit commitments, which may bear risks if numerous (large) customers draw simultaneously on these lines, for example due to a common macroeconomic shock. Thus, we expect for all three that higher shares increase the probability of distress and thus yield positive coefficients. Measuring the managerial quality of the bank is difficult without on-site inspection and resulting qualitative information. Many studies rely instead on cost-income ratios to assess the ability of managers to minimize administrative expenses when generating revenues. But as noted for example by Wheelock and Wilson (2000), high cost-income ratios may merely indicate competitive markets where prices are driven towards marginal cost. Then, cost income ratios contain presumably little information about managerial quality. As an alternative off-site measure, we use cost efficiency scores generated with stochastic frontier analysis. Assuming that markets are competitive, inefficiency arises on the cost side if a bank employs too many input factors or wrong proportions of different input factors. Such deviations would systematically lead to higher than optimal cost. Consequently, we hypothesize that higher cost efficiency reduces the probability of distress. The mechanics to obtain bank-specific estimates from this cost minimization model are provided in the appendix. We capture the profitability of banks by return on equity and account for their liquidity with the ratio of cash and short run net interbank assets relative to total assets. To control for (regional) macroeconomic conditions, we also include the corporate insolvency ratio per federal state and expect that fewer troublesome customers also reduce the distress probabilities of banks.

Only few banks in our sample experienced multiple events over time. Nonetheless, we note that bank distress may very well depend on previous states of distress.[15] Therefore, we control for a bank's previous state of distress by means of a memory variable MEM_j for $j = 2, 3, 4$.[16] This is a dummy variable that takes on a value of one if the bank experienced a (distressed) event j in it's history.[17] In addition, we use a robust sandwich estimator that allows for dependence across yearly observations per bank to obtain standard errors.[18]

[15] The total number of distressed events of 1,119 (table 1) is distributed across 793 banks. 730 are subject to maximal two events during 1995 and 2004. The maximum number of multiple events per bank is six, but applies only to one institute. Excluding banks with multiple events did not affect our results qualitatively.

[16] Note that group $j = 1$ comprise non-distressed bank years. Groups 2 through 4, in turn, represent distress categories I to III.

[17] Obviously, absorbing distress events covered in category IV are not considered.

[18] Ideally, we could specify a generalized ordered logit model as a panel. However, to our knowledge, no such estimator exists for polytomonous response models in general, let alone for the generalized ordered logit. As an additional robustness check we follow Hosmer and Lemshow (2000) and compare for each distress category results from binary logistic regressions with panel estimations

4 Results

We depict results from four hazard rate models in table 3. All four models are nested in the generalized ordered logit model in equation (2). Consider first the simplest case of a basic binomial logit model (column BLT), where all four distress categories are pooled into one dichotomous dependent event. The discriminatory power of this model is high as witnessed by a value of 0.804 for the Area Under the Receiver Operating Characteristics Curve (AUR) and a pseudo R^2 of 14.7%.[19] Coefficient estimates for the various components of banks' financial profiles are highly significant and in line with both expectations and previous results in the literature. Better capitalization, higher profitability and efficiency as well as more favorable macroeconomic conditions all reduce the likelihood of distress. In turn, higher exposures to customer credit and off-balance sheet activities, poor loan quality and excessive liquidity holdings all imply a higher probability of distress. To evaluate the economic significance of individual covariates effects it may, however, be misleading to rely on coefficient estimates alone. Hosmer and Lemshow (2000) suggest to consult instead marginal effects. Before doing so, we test whether this model is the most adequate one available to draw inference.

for dichotomous responses and find hardly any qualitative difference.

[19] AUR values measure the ability of the model to discriminate between event and control group observations for a range of cut-off probabilities from zero to one. Values around 0.7 are considered good, those around 0.8 are excellent (Hosmer and Lemshow, 2000).

Table 3: Hazard estimations of German bank distress

	BLT[1)]	**OLT**[2)]	**GOLT**[3)]				**PPOM**[4)]			
	β	β	β_1	β_2	β_3	β_4	β_1	β_2	β_3	β_4
Equity ratio	-0.039**	-0.040**	-0.045***	-0.058***	-0.027	0.047*	-0.043***	-0.054***	-0.031	0.036
Total reserves	-0.670***	-0.669***	-0.669***	-0.645***	-1.044***	-1.043***	-0.667***	-0.664***	-1.082***	-1.081***
Risky loans	0.022***	0.021***	0.021***	0.020***	0.016***	0.021***	0.021***	0.021***	0.021***	0.021***
Customer loans	0.019***	0.019***	0.019***	0.020***	0.016***	0.015***	0.019***	0.019***	0.019***	0.019***
OBS activities	0.009	0.009	0.01	0.004	0.038***	-0.009	0.01	0.005	0.031**	-0.01
Cost efficiency	-0.012***	-0.011**	-0.012***	-0.006	-0.004	0.001	-0.012***	-0.007	-0.003	0.003
RoE	-0.034***	-0.033***	-0.034***	-0.033***	-0.034***	-0.032***	-0.033***	-0.033***	-0.033***	-0.033***
Liquidity	0.027***	0.028***	0.029***	0.033***	0.029***	0.025*	0.028***	0.028***	0.028***	0.028***
Insolvencies	0.756***	0.702***	0.748***	0.617***	0.489***	-0.233	0.742***	0.637***	0.543***	-0.209
MEM_1	0.028	0.074	0.061	0.033	0.14	0.491	0.083	0.083	0.083	0.083
MEM_2	1.218***	1.150***	1.235***	1.296***	0.511***	0.611***	1.232***	1.297***	0.502***	0.627***
MEM_3	0.683***	0.720***	0.643***	0.735***	0.975***	1.203***	0.655***	0.720***	0.922***	1.125***
α_1	-3.541***	-3.512***	-3.494***				-3.482***			
α_2		-3.603***		-3.796***				-3.789***		
α_3		-4.228***			-4.235***				-4.608***	
α_4		-4.802***				-5.288***				-5.418***
Observations	25,624	25,624	25,624				25,624			
Wald [chi^2]:	1212.75	1294.88	3711.09				3731.55			
Log likelihood:	-3918.97	-5332.16	-5159.12				-5170.17			
Pseudo R^2	0.1477	0.1123	0.1411				0.1393			

Notes: Robust standard errors; *,**,*** denote significant at the 10,5,1 percent level, respectively. For variable descriptions see table 2.

1) Binomial logit model; 2) Ordered logit model; 3) Generalized ordered model; 4) Partial proportional odds model.

Consider to this end next the ordered logit model depicted in column OLT. Category specific intercept estimates confirm that distress events among German banks exhibit a pecking order of ascending severity. All four estimated intercepts exhibit the expected order in terms of magnitude (Greene, 2003; Williams, 2006). All estimated intercepts are significantly different from zero. More importantly, the hypothesis of identical intercepts α_j is also rejected. We report the according χ^2 test statistic as well as p-values from a Wald test of identical intercept coefficients in the top panel of table 4. The six individual tests on significant difference between α_j's yield that differences are unequal from zero. Finally, the hypothesis of joint equality of individual intercept parameters is rejected, too. In sum, specification tests support the use of an ordered logit model as opposed to the more commonly employed binomial logit model.

Table 4: Specification tests for the generalized ordered model

OLT		α_1	α_2	α_3	
α_2	χ^2	86.2			
	p-value	0.000			
α_3	χ^2	542.5	455.3		
	p-value	0.000	0.000		
α_4	χ^2	722.3	648.5	240.2	
	p-value	0.000	0.000	0.000	
All α_i identical					853.34
					0.000
GOLT					
Identical β's	χ^2				372.24
	p-value				0.000
Identical β's and α's	χ^2				811.83
	p-value				0.000
PPOM					
PPOM restrictions	χ^2				24.03
	p-value				0.065

However, it remains at this stage unclear whether slope coefficients differ, too. We consider it likely that, for example, an increase in the equity ratio affects the respective likelihoods of distressed events of different order to varying degrees. As a next specification test, we thus allow all slope coefficients β_j to vary across categories $j = 1, .., 5$. Estimated coefficients from a generalized ordered logit model (GOLT) are depicted for each category in the accordingly labelled columns in table 3. The direction of individual coefficients remains stable compared to the BLT and OLT specification. To interpret individual coefficients note the varying categories contrasted with each other for a change of individual covariates. For example, a coefficient β_1 for equity of -0.045 implies that an improvement of equity ratios reduces the likelihood of distress according to category I or higher relative to not experiencing distress. Likewise, β_2 for equity ratios of -0.058 compares the likelihood of experiencing categories II through IV distress relative to no or only weakest distress according to category I. The χ^2 test statistics of joint identity of slope coefficients on the one hand and of equal slope and intercept coefficients in the mid-panel of table 4 clearly reject these hypotheses at the 1% percent level, respectively. We conclude that hazard rate models for German universal banks should account not only for different degrees of distress but also for the varying effects of changes in financial profiles on these ordered distress categories.

Finally, note that some coefficients exhibit fairly small differences in estimated parameters across categories in table 3, for example return on equity and risky loans. Therefore, we test the so-called partial-proportional odds assumption. The null hypothesis is that some coefficients are equal across dependent categories while other parts of the hazard function do differ. We test for all possible combinations of individual coefficients if slope coefficients across categories are identical and identify four coefficients, which can be restricted. [20] The resulting parsimonious model that we use to draw inference restricts risky and customer loan shares as well as return on equity and one memory variable to be identical across $j = 1, .., 5$. The test statistic at the bottom label of table 4 confirms that the partial proportional odds model (PPOM) does not violate the assumption of non-equal slope coefficients for these covariates at the 5% level.[21]

In sum, the flexible PPOM model adds important qualitative information. First, we note that some covariates are only significant for the likelihood of weaker forms of bank distress. Deteriorating equity ratios and lower cost efficiency decrease only the likelihood of weaker distress events significantly. Likewise, corporate insolvencies as a proxy for macroeconomic conditions seem helpful to indicate signals of early and medium stress but do not help to explain ultimate bank failure in the form of either takeovers or closure. Our results thus suggest that bank exit due to distress depends to the largest extent on bank idiosyncratic factors while only weaker forms of stress are more dependent on the business cycle.

Second, different elements of banks' financial conditions are of varying importance depending on the severity of trouble. Estimated coefficients suggest that the role of reduced total reserves is of increasing importance for worse degrees of distress. In contrast, all other financial ratios that are also significant determinants of worst case distress, exhibit a constant coefficient across all categories. This result implies that banks on the brink of failure react more sensitive to a given deterioration of reserves compared to banks in less troublesome states. This result is important to improve our knowledge regarding which components of banks' financial profiles to

[20] To conserve on space we do not provide all test statistics here. They are available upon request from the authors.

[21] Note, that the log-likelihood for the PPOM is slightly worse compared to the most general GOLT model. Presumably, the gain from more degrees of freedom is too small to compensate for the information lost by imposing the restrictions. For example, the GOLT coefficients on risky loans are almost all identical with the exception of β_3. It depends hence on the significance level chosen whether to impose the constraint in the PPOM or not. Here, we chose the 5% level to test for imposable constraints. A more restrictive approach using the 1% level led as expected to fewer restrictions and also a higher log-likelihood value of the PPOM compared to the GOLT.

address when resolving the most troublesome situations in the banking system.

Third, an important additional determinant of distress in the subsequent period is a bank's history of trouble. On the one hand the weakest form of distress appears to have no discriminatory power between further deterioration of distress versus remaining in or below the current distress category. Potentially, this result suggests that automatically ignited indications of trouble required by law contain only limited information about the true state of the bank. On the other hand, both remaining memory variables indicate that having experienced a distressed event of medium order in the past increases the odds to be subject to an even higher order of stress for a given financial profile. This result suggests that once a bank is somewhat troubled, a further deterioration of it's financial position is more likely than not. Note, however, that our approach here cannot fully explain what distinguishes troubled banks, which manage to recover from those that do manage turning around the bank.[22]

In sum, the parsimonious partial proportional odds model is well suited to estimate different distress probabilities. But to assess economically significant determinants of bank distress categories, we need to consider marginal effects in addition to estimated coefficients. We depict marginal effects for each category $j = 1, ..5$, evaluated at the mean of x, in table 5.

We report marginal effects as semi-elasticities $\delta y / \delta lnx$ evaluated at the mean, which are denoted in basis points in table 4. For example, a reported marginal effect of 0.96 for the equity ratio in group 0 implies an increase in the probability of no-distress by 0.96 basis points due to a 1% increase in the ratio.

Our most important conclusion is that the economic importance of different components of banks' financial profiles differs across distress categories. The changing magnitude and significance of individual marginal effects across distress categories highlights that attempts of bankers and regulators to reduce the likelihood of distress require a more differentiated mix of measures to be effective. Our results confirm that total reserve holdings are of increasing importance to avoid absorbing events in category IV, but have no significant contribution to avoid weakest distress. Strategies aiming to increase profitability are of importance for all four degrees of distress.[23] However, this appears particularly helpful in medium ranges of distress, while final exit PDs can be reduced by as much as 0.88 basis points when reducing the share of customer loans by 1%. Marginal effects of the history of increasingly worse distressed events appear to determine future trouble to a much lesser extent compared to the previously reported coefficient estimates. While this underlines the importance of not relying on the latter only to draw inference, this result also suggests some path dependency for troubled banks.

The likelihood not to experience any distress event is most affected by cost efficient operations and few customer loans. An increase in either measure by one

[22]Such an analysis requires in our view not only a sole focus on troubled banks but also further information on e.g. measures taken by different banks to recover. We consider this research question out of the present paper's scope and postpone the issue to future research.

[23]Since we report semi-elasticities on probabilities of distress, marginal effects also differ for covariates with restricted coefficients (see equation (2)). These would only be identical when reporting effects on scores instead of PD.

Table 5: Marginal effects for the partial proportional odds model

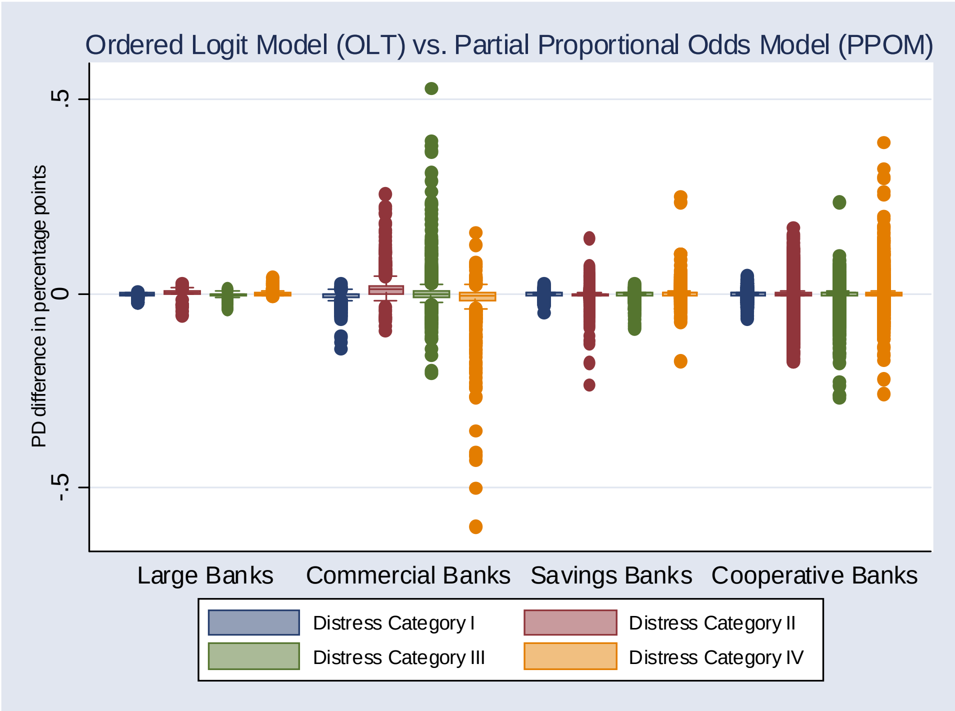
Variable	**Category**					$\bar{x}$
	0	*I*	*II*	*III*	*IV*	
Equity ratio	0.96***	0.15	-0.80***	-0.53 ***	0.22	8.327
Total reserves	1.67***	-0.13**	-0.33***	-0.48 ***	-0.73***	0.937
Risky loans	-0.55***	0.04***	0.27***	0.10 ***	0.15***	11.055
Customer loans	-3.25***	0.24***	1.56***	0.57 ***	0.88***	58.623
OBS activities	-0.08	0.04	-0.08	0.14 ***	-0.02	3.100
Cost efficiency	2.57***	-1.21***	-1.05*	-0.49	0.18	82.927
RoE	1.33***	-0.10***	-0.63	-0.23 ***	-0.36***	14.857
Liquidity	-0.50***	0.04***	0.24***	0.09 ***	0.14***	6.610
Insolvencies	-1.72***	0.35***	0.80***	0.70 ***	-0.13	0.869
MEM_1	0.00	0.00	0.00	0.00	0.00	0.008
MEM_2	-0.12***	0.00	0.09***	0.01	0.02***	0.036
MEM_3	-0.07***	0.00	0.03***	0.01 ***	0.03***	0.038

Notes: marginal effects evaluated at the mean as semi-elasticities $\delta y/\delta lnx$, measured in basis points. *,**,*** denote significant at the 10,5,1 percent level, respectively.

percent, improves the probability of no-distress by 2.6 or 3.3 basis points. Other crucial components of bank's financial profile that increase the likelihood of stability are capitalization, especially reserves, and profitability. While better regional macroeconomic conditions, measured by corporate insolvencies have a significant impact on the probability of no-distress, the magnitude of marginal effects suggests that financial stability is primarily driven by bank-specific factors. In line with estimated coefficients not significantly different from zero, having experienced the weakest kind of distress in the past does not influence the likelihood of further failure significantly. Early warning signals reflected by compulsory notifications appear to have little predictive power of more severe degrees of distress.

Despite statistically significantly different coefficients compared to more restricted hazard models as well as economically significant marginal effects, the usefulness of the PPOM regarding rating banks in the industry may be doubted. One may argue that the direction and magnitude of estimated coefficients reported for the binomial and ordered logit models in table 3 does not differ substantially. For rating purposes, it is therefore also interesting to compare resulting distributions of probabilities of distress. Consider to this end figure 1, which depicts box plots of the differences between probabilities of distress between the ordered and the partial proportional

Figure 1: Differences in probabilities of distress according to OLT and PPOM



odds model.[24]

Figure 1 illustrates the added information in contrast to dichotomous hazard rate models. The partially restricted generalized ordered model add allows us to assess probabilities per distress category, which we depict here per banking group. Predicted probabilities of distress differ up to 60 basis points between the preferred PPOM and the less flexible ordered logit model with common slope coefficients. Given an expected overall frequency of 4.4 percentage points (see table 1), this difference is economically significant and suggests a more differentiated view of distress when rating banks.

Consider also differences in PD's between models per banking group. It is first of all important to note that for large banks both models do not yield very different results. This is comforting since it implies that especially for this important group of banks potential specification problems due to the neglect of different orders of distress seem small.[25]

[24]We do not depict distributions of probabilities of distress for reasons of confidentiality.

[25]Note that this result merely reflects a similar appropriateness of both models to estimate large bank distress. It need not imply that either is particularly suited. Given the low number of observations of large banks in general and that of only few distressed events in particular, we therefore caution to use only bank-specific point estimates for large banks of either hazard model to assess these bank's riskiness. Instead, regulators are certainly well advised for this group to rely

Differences between models regarding local cooperative banks seem fairly moderate since they do not exceed 25 basis points. However, even such a difference in PDs may already influence a bank's rating and thus refinancing cost substantially. In turn, estimated PD differ the most for the group of commercial banks and, to a lesser extent, for local savings banks. More specifically, allowing hazard functions to differ in individual covariate sensitivities yields markedly different PD for the worst distress category. Since such absorbing distress events most likely cause the largest cost to society, it seems conservative to avoid the danger of underestimating these events. While differences between OLT and PPOM are distributed rather symmetric for savings banks, worst category distress PD for commercial banks seem more often than not to be lower according to the more restricted OLT model compared to the suggested PPOM. Hence, we deem it prudent to at least consider this model in addition to more restricted hazard models when rating banks.

5 Conclusion

In this paper we suggest a generalized ordered logit model to estimate probabilities of distress among German universal banks. Our sample includes commercial, savings and cooperative banks that reported to the Bundesbank between 1994 and 2004. We distinguish four different categories of distress events and group them in ascending order of severity of distress: (i) compulsory information of regulatory authorities about potential threats; (ii) warning measures issued by regulatory authorities; (iii) capital injections by sector insurances and binding measures of regulatory authorities; (iv) restructuring mergers and forced closure initiated by regulatory authorities.

We identify a vector of bank-specific and regional macroeconomic variables that predicts probabilities of distress with high accuracy. We test if the model can be reduced to both a binary or ordered logit regression and reject both hypotheses. Thus, our results support, first, the ordinal nature of different distressed events and, second, the different sensitivity of given changes of banks' financial profiles on different events, respectively.

Our results suggest that loan quality, cost efficiency and capitalization are of importance to explain weak orders of distress. However, deteriorating conditions according to the latter two indicators have little explanatory power for more severe distress events, which depend primarily on the former and total reserve holdings as well as profitability.

We also find evidence that banks with a history of financial trouble are significantly more likely to be distressed in the future, too. While having experienced only the weakest form of bank distress appears to have little implications for future deteriorations of a bank's stability, especially medium degree distress events in the past contribute to larger probabilities of further distress. We conclude that it is difficult to turn around a bank once certain degrees of distress have been surpassed. Thus,

on multiple sources of information, such as more intensive on-site examinations rather than off-site rating systems in general.

further research investigating the determinants of successful restructuring seems appropriate.

Apart from statistically significant evidence on estimated parameters in line with previous evidence on bank failures, our results for marginal effects show that especially the total reserves ratio and the customer loans ratio are of high economic significance. A one percent increase of the former decreases the likelihood to exit due to failure by 0.73 basis points. Likewise, a one percent improvement in the share of customer loans reduces this PD by 0.88 basis points. In turn, corporate insolvency ratios that measure the health of the regional corporate sector have no significant influence on worst case distress events of banks. Hence, especially higher order distress events appear to depend only indirectly at best on (regional) macroeconomic conditions.

Finally, our results pertain that the generalized ordered logit model's predictions differ at times substantially from restricted (ordered) logit analysis. We find that, depending on banking group and distress category, estimated PDs between the two models differ up to 70 basis points, which accounts for 20% of the observed mean probability of distress. Moreover, our results highlight the foregone informational value of less restricted models since individual covariates influence different distress events to varying extents. With respect to managing bank risks this finding may be useful for bankers and regulators.

In sum, the generalized model suggested in this paper allows a more differentiated view of distressed events in banking. Future hazard studies should consider to model the pecking order of distress as well as differing sensitivities to financial bank profiles more explicitly.

6 Appendix: Cost efficiency estimation

To approximate the management qualities of banks we use the concept of X-efficiency introduced originally by Leibenstein (1966) and applied to bank efficiency measurement in a number of studies (Berger et al., 1993; Berger and Humphrey, 1997; Amel et al., 2004). We assume that a bank k uses fixed assets x_1, labor x_2 and borrowed funds x_3 to produce three outputs: customer y_1 and interbank loans y_2 and financial securities y_3. If banks are price takers, they minimize cost C subject to given input prices w_i and production technology $T(\bullet)$, which depends on y, x, and further controls z. Input prices are calculated as in Koetter (2006) per regional market: depreciation over fixed assets for w_1, personnel expenses over full time equivalents w_2 and total interest expenditure over total borrowed funds w_3. To account for technical change we further specify a general time trend t and include interaction terms with outputs, input prices and controls. The solution to this cost minimization problem yields an optimal cost function$C*(w,y,z)$, which we estimate with the following translog specification:

$$
\begin{aligned}
\ln C_k \; = \;& \alpha_0 + \sum_{i=1}^{3} \alpha_i \ln w_{ik} + \sum_{m=1}^{3} \beta_m \ln y_{mk} + \delta_r \ln z_{kr} \\
& + \frac{1}{2} \sum_{i=1}^{3} \sum_{j=1}^{3} \alpha_{ij} \ln w_{ik} \ln w_{jk} + \sum_{i=1}^{3} \sum_{m=1}^{3} \gamma_{im} \ln w_{ik} \ln y_{mk} \\
& + \frac{1}{2} \sum_{m=1}^{3} \sum_{n=1}^{3} \beta_{mn} \ln y_{mk} \ln y_{nk} + \frac{1}{2} \pi_r (\ln z_{kr})^2 \\
& + \sum_{i=1}^{3} \omega_i \ln w_{ik} \ln z_{kr} + \sum_{m=1}^{3} \zeta_m \ln y_{mk} \ln z_{kr} + \eta_0 t + \frac{1}{2} \eta_1 (t)^2 \\
& + \sum_{i=1}^{3} \kappa_i \ln w_{ik} t + \sum_{m=1}^{3} \tau_m \ln y_{mk} t + \theta_r \ln z_{kr} t + \varepsilon_k .
\end{aligned}
\tag{4}
$$

After imposing the necessary homogeneity and symmetry restrictions (Koetter, 2006), we estimate equation (4) as a stochastic cost frontier. Any bank k can deviate from optimal cost due to random noise, v_k, or inefficient use of in- and outputs, u_k. We specify a composed total error, ε_k. For a cost frontier inefficiency leads to above frontier costs. Therefore, the total error is $\varepsilon_k = u_k + v_k$. The random error term v_k is assumed $i.i.d.$ with $v_k \sim N(0, \sigma_v^2)$ and independent of the explanatory variables. The inefficiency term is $i.i.d.$ with $u_k \sim N|(\mu, \sigma_u^2)|$ and independent of the v_k. It is drawn from a non-negative distribution truncated at μ. Descriptive statistics to estimate equation (4) are depicted in table 6.

We obtain bank-specific efficiency measures as suggested by using the conditional distribution of u given ε (Jondrow et al., 1982). A point estimator of technical efficiency is given by $E(u_k|\varepsilon_k)$, i.e. the mean of u_k given ε_k. Cost efficiency per bank and year is calculated as $[\exp(-u_k)]$ and equals one for a fully efficient bank. Likewise, CE of 0.9 implies that a bank could have produced an identical output vector with 90 percent of actually incurred cost.

Table 6: Bank production data of German universal banks 1994-2005

Variable SFA		**Mean**	**SD**	**Min**	**Max**	**N**
Interbank loans	y_1	289.5	3747.5	0.001	146000	30,307
Customer loans	y_2	640.8	4901.0	0.002	210000	30,307
Securities	y_3	287.1	2667.4	0.003	130000	30,307
Price of fixed assets	w_1	14.6	5.4	5.059	75.71	30,307
Price of labor	w_2	50.7	7.1	30.157	97.81	30,307
Price of borrowed funds	w_3	3.5	0.6	1.776	5.55	30,307
Equity	z	50.2	380.6	0.252	16100	30,307
Total operating cost	TOC	66.2	548.1	0.261	22300	30,307

Notes: All outputs, equity and operating cost measured in millions of Euro; prices of fixed assets and borrowed funds in percent; price of labor in thousands of Euro;

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