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Distress in European Banks: An Analysis Based on a New Data Set

Tigran Poghosyan and Martin Čihák

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Prepared by Tigran Poghosyan and Martin Čihák[1]

Authorized for distribution by Luc D. Everaert

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Abstract

The global financial crisis has highlighted the importance of early identification of weak banks: when problems are identified late, solutions are much more costly. Until recently, Europe has seen only a small number of outright bank failures, which made the estimation of early warning models for bank supervision very difficult. This paper presents a unique database of individual bank distress across the European Union from mid-1990s to 2008. Using this data set, we analyze the causes of banking distress in Europe. We identify a set of indicators and thresholds that can help to distinguish sound banks from those vulnerable to financial distress.

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Authors' E-Mail Addresses: t.poghosyan@rug.nl; mcihak@imf.org

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I. Introduction

The ongoing global financial turbulence has highlighted the importance of early identification of weak banks: when problems are identified late, solving them is much more costly. In this paper, we create a database of observed situations of distress in European Union (EU) banks, and use that database to build an early warning system for bank distress.

Comprehensive data on bank distress have, to our knowledge, not yet been made publicly available on an EU-wide basis. Most of the existing literature on bank distress focuses on the United States, which had numerous bank failures that provide a rich data set for a "forensic" examination of the determinants of distress; relevant papers are available also for some emerging markets that have experienced waves of bank failures.[2] However, there is no literature on predicting bank failures in the EU as a whole.[3] This most likely reflects the fact that the number of bank failures in EU countries was relatively low (at least until recently), and some EU countries had no bank failures at all. In this paper, we address this challenge by covering, in a consistent manner, banks in all EU countries, thereby creating a much wider sample than would be possible by analyzing only a single country or a smaller set of countries. The benefit of our approach is that, even if some parts of the EU experienced no bank distress, distress situations in other parts of the EU can provide a useful benchmark, after controlling for cross-country differences. Additionally, recent months have provided some high-profile cases of bank distress, which are all included in the database.

Based on this database, and using an extensive panel data on individual EU banks (including those that have and those that have not experienced distress), we analyze the causes of bank distress in Europe. This could be a basis for finding suitable "benchmarks" of banking soundness in the EU. We identify a set of indicators and thresholds ("trigger points") that can help to distinguish sound banks from those that are weak. We subject this model to a wide range of robustness tests and examine its performance with respect to the most recent observations of bank distress.

Having such a model is certainly important. It is helpful for depositors and other creditors, who stand to lose financially if a bank fails. It is potentially useful for rating agencies trying to identify weak and strong financial institutions. Finally, it is also very useful for prudential supervisors, who are tasked with ensuring the safety and soundness of financial institutions. If a bank is flagged as "weak" by the early warning system, it should be a signal for the supervisors to focus on that institution in more detail, and, if questions about the soundness

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[2] Examples of this research include Martin (1977) and Calomiris and Mason (2000) for the United States, Gonzalez-Hermosillo, Pazarbasioglu, and Billings (1997) for Mexico, Persons (1999) for Thailand, and Kraft and Galac (2007) for Croatia.

[3] There are some recent studies analyzing banking distress in Germany (Kick and Koetter, 2007 and Koetter and others, 2007). However, these studies focus only on a single country rather than the EU.

of that institution persist, to enforce a corrective action (which may in an extreme case include taking over the bank).

Having such a framework is particularly useful in the EU, given its degree of financial integration, its stated goal of promoting further financial integration, and its supervisory arrangements, which are still country-by-country based. An EU-level early warning system based on a model of this kind could provide a useful benchmark for bank soundness. Ideally, these benchmarks should be widely disseminated to increase transparency and comparability across the EU financial system. Ultimately, if this system worked reasonably well over a period of time, the authorities could consider moving from the existing country-by-country approach, which allows country-level supervisory discretion and forbearance, toward a system that is more rules based and more uniform across the EU.[4] Such a framework would be in line with the EU authorities' stated goal of promoting European financial integration.

To briefly preview our main findings, our paper lends empirical support to the proposition of establishing EU-wide benchmark criteria for banking sector soundness. Based on a rigorous analysis of past instances of bank distress, we show that it is possible to establish plausible sets of thresholds for increased attention by supervisors (and other market participants). The analysis also illustrates that relating those thresholds only to capital adequacy is insufficient, and that one needs to include combinations of several relevant variables to capture the riskiness of individual institutions.

The structure of the paper is as follows. Section II overviews the relevant literature on early warning systems for banking supervision, and discusses the practical uses of such systems. Section III explains the estimation methodology and the data being used. Section IV presents the estimation results. Section V concludes.

II. Literature Overview and Motivation

A. Early Warning Systems for Banking Soundness[5]

A survey of the relevant literature suggests that leading indicators of bank distress can be grouped into three main categories. The first category consists of standard balance sheet and income statement financial ratios. This includes the so-called CAMEL variables (where CAMEL stands for "capital, asset quality, management, earnings, and liquidity"). These variables are very popular in the "supervisory risk assessment and early warning systems"

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[4] There are of course some limits to rules-based systems. For example, banks may be able to bypass the rules, especially if the rules become too cumbersome. But this is an argument for designing rules that are relatively simple and easy to enforce, rather than for moving from rules to discretion.

[5] This section provides a brief overview of this body of work; additional information is provided in Appendix I. There is a related, but separate, literature on early warning systems for predicting currency crises and systemic banking crises. For a survey, see, e.g., Berg, Borensztein, and Pattillo (2004).

used by supervisory agencies around the world. Asset quality indicators usually play an important role in early warning models, particularly in models that focus on the medium- to long-term horizon. In the short run, profitability, liquidity, and solvency indicators provide helpful information on a bank's financial condition (see Appendix I for details).

There is a relatively broad agreement in the literature and among practitioners that the CAMEL indicators are useful in grading banks in terms of their financial vulnerability, and supervisors often combine these indicators to come up with an assessment of a bank's soundness. However, there is no clear agreement in the literature on how exactly to combine the various CAMEL indicators into a "bottom-line" assessment of bank soundness, and these measures are rarely "back tested" on actual distress situations. Moreover, there is also some evidence that traditional CAMEL grades have some limits in predicting bank failure (e.g., Rojas-Suarez, 2001), and need to be complemented by other indicators.

The second category of leading indicators of bank distress consists of market prices of financial instruments, such as bank stocks and subordinated debt. Studies based on U.S. bank data suggest that market price-based indicators contain useful predictive information about bank distress that is not contained in the CAMEL indicators (e.g., Flannery, 1998; Curry, Elmer, and Fissel, 2003).The literature for non-U.S. banks is less conclusive (e.g., Bongini, Laeven, and Majnoni, 2002; Čihák, 2007).

The third category of potential leading indicators contains other, somewhat less common, measures of bank risk and financial strength, such as deposit rates (see, e.g., Kraft and Galac, 2007) or indicators characterizing the economic environment in which the banks operate.[6]

B. Examples of Uses of the Early Warning Systems

There are two main potential uses for early warning systems. The first one relates to strengthening the role of rules in banking supervision, and decreasing the scope for discretion in decision making. The second one relates to market discipline.

Potentially, a well-functioning supervisory risk assessment and early warning system could be linked to a set of corrective actions that get progressively stronger as the bank reaches more trigger points. With a few exceptions, most notably the Federal Deposit Insurance Corporation (FDIC) in the United States (FDIC, 2003; Jones and King, 1995), there is as yet no such automatic and direct link in most of the supervisory risk assessment and early warning systems with formal prompt corrective action frameworks. Financial institutions identified as potentially risky by the systems are typically subjected to greater supervisory surveillance and on-site examination before enforcement of formal actions is initiated. However, as the reliability of the systems' output increases, it would be useful to establish

[6] Rating agencies' assessments could also be considered in this category, even though these are typically based on a combination of financial ratios and market indicators.

such a direct link between the output and formal corrective action, to limit the scope for supervisory forbearance. Indeed, a survey of supervisory early warning systems around the world (Appendix I) indicates that although supervisory authorities have been moving towards more formal, structured and risk-focused procedures for ongoing banking supervision, there is still substantial scope for deviations.[7]

In the EU context, there are additional reasons for moving towards a more rules-based framework. If such a framework, requiring supervisors to intervene at certain trigger points, were implemented at the EU level, it would give more confidence to supervisors in one EU member country that timely intervention will take place by supervisors in another EU member country. Nieto, Mayes, and Wall (2008) provide an overview of the prompt corrective action (PCA) framework employed by the U.S. FDIC. They argue that implementing a PCA-like framework might be able to address some of the issues relating to the coordination among the national supervisors in Europe (Appendix III provides more details on this idea). Of course, this early warning system will have to be used wisely, because a purely mechanical application could allow banks to bypass the framework by creative accounting or other types of misreporting. Also, the early warning system of course cannot be cast in stone forever. As suggested in a different context by King, Nuxoll, and Yeager (2006), it needs to be reestimated and reassessed to respond to new developments in the system—a point particularly relevant in today's European banking market.

An important feature of the financial stability framework in the EU is that supervisors in individual EU member countries have different approaches to dealing with weak banks (Čihák and Decressin, 2007). These cross-country differences may be warranted for small banks with mostly local operations, but they may become an issue for the large cross-border financial institutions (LCFIs) that dominate the EU financial landscape.[8] The legal, regulatory, and supervisory frameworks have not been able to keep up with this rapidly growing cross-border presence.

The second potential use of the early warning system is that publishing banks' performance with respect to the early warning system would also enhance market discipline. It would make clear to the depositors, creditors, rating agencies, and other market participants at which point a bank is entering a dangerous territory. Ultimately, this would lower the burdens to be shared in the case of a failure. Along these lines, and invoking the Maastricht criteria that serve as benchmarks for good macroeconomic performance, Lannoo (2008) calls

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[7] This finding is consistent also with recent surveys of supervisory and regulatory practices by Čihák and Tieman (2006 and 2008), showing that there are still substantial differences between the regulations "on the book" and their implementation in the field.

[8] The EU has a developed banking system with some 8,000 banks. Within this group, major LCFIs are emerging. Forty-six LCFIs hold about 68 percent of EU banking assets; of these, 16 key cross-border players account for about one-third of EU banking assets, hold an average of 38 percent of their EU banking assets outside their home countries, and operate in just under half of the other EU countries (Appendix II).

for introducing "Maastricht criteria" for financial institutions. As with the Maastricht criteria, which set debt and deficit limits for public finances and seek balanced budgets in the medium term, European authorities should in his view agree on a set of easily understandable standards to measure the quality of a bank's finances. These criteria could include liquidity, the regulatory capital requirement, asset diversification ratios, and measures of good corporate governance. In each case, there would be a minimum rate as well as a target rate—a more ambitious standard to which banks should aspire in the long term.

A key part of these proposals is that the "benchmark" of sound bank management practices would be based on a set of criteria that the relevant readers can understand, and this information would be continuously disclosed. The difference from conventional rating agencies would be that these standards would be more transparent and more accessible to financial analysis. These targets should not be too difficult to calculate, as bank analysts commonly use them. Hence, a bank that uses depositors' funds for risky trading positions would have a higher cost of financing than a bank with a low risk profile, as other banks would be hesitant to lend to this bank and customers to deposit their savings there. In other words, this could stimulate peer pressure and market discipline.[9]

III. Methodology and Data

A. Estimation Methodology

To evaluate the impact of various financial indicators on the probability of bank distress (PD), we use several versions of the logistic probability model. Let Y_{ijt} denote a dummy variable that takes the value of one when bank i headquartered in country j experiences financial distress in time period t and zero otherwise. We estimate the PD as a function of lagged explanatory variables X_{ijt-1}.[10] If we assume that $F(\beta' X_{ijt-1})$ is the cumulative probability distribution function evaluated at $\beta' X_{ijt-1}$, where β is a vector of coefficients to be estimated, then the likelihood function of the model is

$$LogL = \sum_{t=1}^{T}\sum_{i=1}^{N}\left\{Y_{ijt}\log\left[F(\beta' X_{ijt-1})\right] + (1-Y_{ijt})\log\left[1-F(\beta' X_{ijt-1})\right]\right\}, \tag{1}$$

[9] A possible counterargument is that if "too much" information on bank soundness becomes publicly available, it might trigger bank runs. This argument would be relevant if there were a sudden release of detailed and damaging information about a bank. However, the "benchmarks" described here represent an evolutionary, rather than revolutionary, change towards more transparency. The very point of the increased transparency is that, over the medium term, it will push banks into behaving more prudently, in order to limit the risk of runs.

[10] In the baseline estimate, we lagged the explanatory variables by one period, i.e., one year. As a robustness check, we also experimented with two-year and three-year lags. These checks yielded very similar results, but weaker in terms of statistical significance (especially for the three-year lags), suggesting that the predictive power of the explanatory variables declines as we attempt to predict failures further into the future.

where $t=1,\ldots,T$ is the number of time periods, and $n=1,\ldots,N$ is the number of banks.

The sign of the β coefficients indicates the direction of the impact of a marginal change in the respective explanatory variable on the PD. The magnitude of the impact depends on the initial values of the other explanatory variables and their coefficients.

The logistic (logit) model can also be represented in the form of the log odd's ratio,

$$\log \frac{P_{ijt}}{1-P_{ijt}} = \beta_0 + \sum_{k=1}^{K} \beta_k X_{k,ijt-1} \quad , \tag{2}$$

where $P_{ijt} = Prob(Y_{ijt}=1|X_{ijt-1})$ is the probability that bank i located in country j will experience distress in period t, given a vector of K explanatory variables X_{ijt-1}. The left-hand-side expression is the log odd's ratio, measuring the probability of bank distress relative to the probability of no distress. This specification illustrates that the slope coefficients β_k measure the linear impact of the k^{th} explanatory variable on the log odd's ratio, while the impact on the PD depends on the initial values of the explanatory variables $X_{k,ijt-1}$ and their coefficients β_k. Therefore, to assess the economic magnitude of the relationship between explanatory variables and the PD, we will evaluate the marginal impact at the sample mean (which is a common approach in the literature).

The logit model can be estimated in several ways. The simplest logit model assumes independence of errors across individual banks, countries, and time. In practice, this assumption is likely to be violated, especially in the case of the panel structure of the data. Neglecting the violation of the independence of errors assumption leads to downward biased estimates of standard errors of the coefficients. To correct for the violation of the independence assumption, we employ a heteroscedasticity robust variance-covariance matrix, which allows for the possibility of correlated errors within banks.

Another approach that we also use to exploit the panel structure of the data is to estimate a random effects logit model. The random variation of the intercept can be either across individual banks i (β_0+u_i), or countries j (β_0+u_j), where the random variable u is normally distributed, with mean zero and variance σ^2_u. In economic terms, one can describe the intercept β_0 as a "baseline hazard" of bank PD, that is, the remaining probability of bank distress after controlling for the impact of financial ratios. The significance of the variance of the random intercept σ^2_u can confirm the heterogeneity of the baseline hazard at the individual bank level or the country level.

B. Data

We compile a unique data set on distress in EU banks, using two main sources of information. The first source is Bureau Van Dijk's BankScope database, from which we extract financial data on 5,708 banks in the EU-25 countries in 1996–2007.[11] We combine this with the second source, which is a unique set of data on bank distress. To put together this database, we run detailed searches on the individual banks in the NewsPlus database. The NewsPlus database is powered by Factiva, a Dow Jones company, and provides global news and business information. This continuously updated database contains articles and reports from thousands of local and global newspapers, newswires, trade journals, newsletters, magazines and transcripts.[12]

The NewsPlus/Factiva searches were performed individually for each of the 5,708 banks, and for each year, using a combination of the bank name and a set of keywords designed to capture references to failing banks: "rescue," "bailout," "financial support," "liquidity support," "government guarantee," and "distressed merger." When a search for a particular bank led to a hit (or a number of hits), we examined the highlighted media reports in more detail, to confirm that the above keywords indeed related to this bank and not to another institution. Additionally, we searched websites of the relevant supervisory authorities for references to banks that failed. Based on all these searches, we created a bank distress dummy variable (Y_{ijt}), equal to 1 if there is (at least one) reference to distress in the particular bank in that particular year, and 0 otherwise. Using this strategy, we identified 79 distress events for 54 EU banks during 1997–2008 (the data set on distress events starts and ends one year later than the financial data set , because we examine the relationship between lagged financial variables and observed distress).

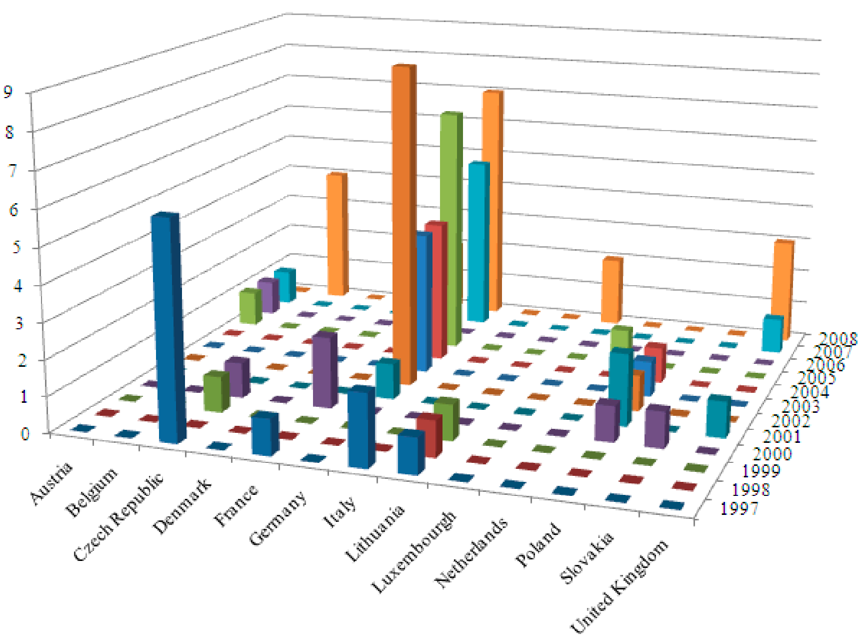
Underlying the NewsPlus/Factiva searches is the notion that a bank is in distress when negative items start to be reported about it in the media. This is of course not the only possible definition of distress, and some banks might go through a period of distress without the media's noticing. (To correct for some banks "flying under the radar," we carried out NewsPlus/Factiva searches for the names of all the EU banks in our list, and, as a robustness check, we rerun our models excluding observations on banks for which these searches returned no hits.) Defining bank distress through the lens of media reports is crude, but it is a relevant notion of bank distress for supervisors and policymakers, who are certainly not keen to see media reports about banks being in trouble. There is therefore a good case for using this approach to analyze causes of bank distress in Europe. (Also, it is a definition that is relatively consistent across the EU, because the NewsPlus/Factiva database covers reasonably well the main business media across the EU countries. In contrast, internal supervisory definitions of banks in distress differ across the EU countries.)

[11] Romania and Bulgaria are excluded, since they joined the EU only in 2007. As regards the "new EU member states" that entered the EU in 2004, the benchmark specification includes all their observations, because their economies were characterized by a high degree of integration with the "old" EU countries even prior to their entry. One of the robustness checks we do consists of excluding pre-2004 observations in these countries.

[12] The Factiva contains a collection of 14,000 sources, including the *Wall Street Journal*, the *Financial Times*, Dow Jones and Reuters newswires, and the Associated Press, as well as Reuters Fundamentals, and D&B company profiles (for details, see www.factiva.com).

The database contains 5,708 banks from the EU-25 countries in our sample, with 29,862 bank-year observations in total (Table 1). The NewsPlus/Factiva search resulted in hits for more than one-half of banks in our sample. We identified 79 distress events for 54 banks, meaning an average distress frequency of about 0.3 percent per year (the number of banks is smaller than the number of distress events, since some banks experienced multiple distress events over time). The distress observations are distributed far from evenly across the EU countries and across years (Figure 1). Most of the distress episodes occurred in Germany, which is also the EU country with the largest number of banks in the sample. Most of the distressed banks are commercial, but there are also some specialized banks and credit institutions.

Figure 1. Overview of Distress Events by Year and by Country, 1997–2008



Source: authors, based on searches in NewsPlus/Factiva
Note: For EU countries that are not shown, no bank distress was identified in the sample period.

Table 1. Database Overview

Country name	Bank-Year Observations			Banks		
	Distressed	Total	No-hitters	Distressed	Total	No-hitters
Austria	3	1,733	325	1	286	58
Belgium	4	505	94	4	100	23
Cyprus	0	99	8	0	18	2
Czech Republic	7	138	15	7	29	3
Denmark	1	795	569	1	115	81
Estonia	0	39	0	0	5	0
Finland	0	74	7	0	18	2
France	7	2,918	2,147	6	534	404
Germany	37	15,938	3,388	20	2623	631
Greece	0	117	34	0	31	10
Hungary	0	132	71	0	25	16
Ireland	0	173	96	0	45	21
Italy	2	2,720	2,358	2	876	765
Latvia	0	164	17	0	22	3
Lithuania	3	87	9	2	12	1
Luxembourg	2	764	626	2	148	124
Malta	0	49	31	0	7	5
Netherlands	1	286	176	1	72	44
Poland	6	241	11	3	45	3
Portugal	0	99	55	0	30	18
Slovakia	1	124	0	1	21	0
Slovenia	0	107	34	0	19	8
Spain	0	744	503	0	237	175
Sweden	0	597	506	0	118	101
United Kingdom	5	1,219	618	4	272	141
Total	79	29,862	11,698	54	5,708	2,639

Source: authors, based on BankScope and NewsPlus/Factiva.

We use financial indicators of banks to generate determinants of bank distress (X_{ijt-1}). Following the established literature and supervisory practice, we start with determinants that are related to the capitalization, asset quality, managerial skills, earnings, and liquidity (CAMEL) of banks. We then proceed to introduce other potential determinants, such as those relating to depositor discipline, contagion effects among banks, the macroeconomic environment, banking market concentration, and the financial market.

The first CAMEL covariate is capitalization, which is measured as the ratio of total equity to total assets. This ratio is popular in the early warning models, the intuition being that a lower equity-to-asset ratio means higher leverage, which makes the bank less resilient to shocks (such as a sudden decline in the value of the bank's assets), other things being equal. We use a simple (unweighted) leverage ratio (as done frequently in banking literature) rather than the ratio of regulatory capital to total risk-weighted assets. The reasons are both practical and conceptual. The main practical reason is that this ratio is not available on a consistent basis for the whole sample: there are too many gaps in this variable in the BankScope database. One conceptual reason is that the weights used to calculate the risk-weighted assets are relatively arbitrary, rather than based on an explicit model of risk (at least that was the case in the period under observation). Moreover, it can be shown that if the amount of required capital depends on the level of risk reported by the banks, supervisors have a limited ability to identify or to sanction dishonest banks (Blum, 2008). In such a situation, a risk-insensitive leverage ratio can be useful.[13] Indeed, recent policy discussions and steps taken in several countries (most prominently in Switzerland) have led to a renewed emphasis on the basic leverage ratio as an important indicator of bank soundness.

As regards the second CAMEL covariate, asset quality, the specification is again based on a combination of practical and conceptual considerations. Data on the stock of nonperforming loans and loan loss reserves are not available for a majority (about 75 percent) of the sample. Therefore, we proxy asset quality by the ratio of loan loss provisions to total loans. The managerial quality of the bank, the third CAMEL covariate, is approximated by the cost-to-income ratio, with lower values of this indicator suggesting better managerial quality. To measure bank earnings, the fourth covariate, we use the standard measure of (after-tax) return on average equity (ROE); in robustness checks, we also include (after-tax) return on average assets (ROA). Liquidity, the fifth covariate, is measured by the ratio of liquid assets to deposits and short-term funding.

In addition to the CAMEL covariates, we also include a number of other potential explanatory variables. Specifically, to approximate market discipline imposed on banks by depositors, we include the average deposit rate of banks, approximated by the ratio of total interest expenses to total deposits. Based on the previous literature on this topic (e.g., Kraft and Galac, 2007), we expect higher deposit rates to be correlated with higher probabilities of distress.

Another additional variable tries to capture contagions among banks. Bank failures are generally rare, but tend to appear in clusters (see, e.g., Hardy, 1998). To capture the clustering of bank failures, we incorporate in our estimates a “contagion dummy” that takes the value of 1 for a bank if there was a failure in a similar bank. A similar bank is defined as a bank in the same country with a similar size (total assets within the range of EUR ±200 million). The range is meant to capture the impact of the contagion effect spreading from an individual bank distress on its peers with comparable market size. Based on this range, we identified 98 banks that are exposed to possible contagion effects. Our results are robust with respect to the choice of the range.[14]

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[13] Relatedly, Gropp and Heider (2008), examining a sample of banks and nonbank corporations in Europe and the United States, and using a simple leverage ratio, are unable to detect first order effects of capital regulation (imposed on the risk-weighted capital adequacy ratio) on the capital structure of banks. They find that the standard cross-sectional determinants of firms’ capital structures valid for nonbank corporations also apply to large, publicly traded banks.

[14] We performed two robustness checks. First, we defined “similar size” as ±100 million Euro rather than ±200 million euro. Second, we used the share of loans to total assets, with a ± 5 percent band, as an alternative

(continued…)

For various robustness checks, we add a number of additional independent variables, which include a set of macroeconomic variables (at the country level, gathered from the IMF's *International Financial Statistics*), a measure of market concentration (calculated from the BankScope data), stock market indicators (downloaded from DataStream), and other variables (see Section IV.B for details).

Table 2 provides a basic analysis of the main determinants of bank distress.[15] It contains mean values for the determinants of financial distress for two groups of bank-year observations: distressed and nondistressed. It shows that, on average, the distressed banks have a lower level of capitalization and earnings and a higher level of loan loss provisions, cost to income ratio, liquidity and implicit deposit rate. A similar pattern holds for the median values of these variables. The comparison of medians suggests that all of them, except for the loan loss provisions and liquidity ratios, are significant at the 5 percent confidence level. The comparison of means suggests significant differences only for the loan loss provisions and implicit deposit rate. However, given the wide heterogeneity of the sample, fat tails, and skewness, the comparison of medians is more informative and provides a more precise picture. To analyze the determinants of bank distress more formally, we turn to regression analysis, which is the subject of the next section.

Table 2. Determinants of Bank Distress

	Nondistressed		Distressed		Mean Equality Test (*t*-test, unequal variances)		Median Equality Test (Wilcoxon test)	
	mean	median	mean	median	difference	*p*-value	difference	*p*-value
(Total equity)/(Total assets)	0.0778	0.0583	0.0445	0.0350	-0.0333	0.1776	-0.0233	0.0000
(Loan loss provisions)/(Total loans)	0.0076	0.0058	0.0293	0.0047	0.0218	0.0045	-0.0010	0.2982
(Total costs)/(Total income)	0.7953	0.8068	1.1334	0.8919	0.3381	0.3985	0.0851	0.0006
(Profit before taxes)/(Total equity)	0.1120	0.1034	-0.2566	0.0245	-0.3685	0.1751	-0.0789	0.0000
(Liquid assets)/(Total assets)	0.2700	0.2288	0.3205	0.1908	0.0505	0.2520	-0.0380	0.6079
(Interest expences)/Deposits	0.0440	0.0330	0.1240	0.0730	0.0799	0.0000	0.0401	0.0000

Note: the null hypothesis of the equality of means/medians test is the equality of means/medians.

measure of similarity. Our estimation results do not change when these alternative definitions of similarity are used to evaluate the impact of contagion (the results are available upon request).

[15] To alleviate the impact of extreme observations and errors in the sample, all these independent variables are winsorized at the 1 percent level.

IV. Estimation Results

A. Baseline Estimate

We start by pooling observations for individual banks and estimating (2) using a logistic model that is robust to heteroscedasticity.[16] The baseline estimation result is shown in column (I) of Table 3.

The results suggest that, in line with economic theory, the PD is negatively associated with the level of bank capitalization and earnings. Banks that are better capitalized and have good earning profiles are less likely to experience distress in the upcoming year.

Similarly, the PD is inversely related to asset quality. Assuming that the higher loan loss provision profile implies a riskier loan portfolio, the positive sign for this variable indicates that the PD is influenced by the deterioration of the loan portfolio.

We also find significant evidence in favor of the market discipline hypothesis. Those banks that "bargain for resurrection" in difficult times by increasing their deposit rates are more likely to experience financial distress in the next year. This finding is in line with some of the recent research on other countries, for example with the results of Kraft and Galac (2007).

The coefficient of the contagion dummy variable came out positive and was highly significant. This suggests that financial distress in a bank not only influences the bank itself, but it also significantly increases PDs of its peers in the market.

The baseline estimation results suggest that managerial quality is not a significant factor for bank PDs. As regards managerial quality, it is possible that the results would be different if we used a more direct measure of cost efficiency of a bank, a measure generated by the stochastic frontier analysis. However, introducing such a measure is unlikely to have a major impact, and it would make the model substantially more complex to implement and to explain to an outsider, which would not be in line with the intended uses of the model. For the same reason, the cost-to-income ratio that we employ is a widely used measure of bank's managerial quality. The fact that it does not come out significant suggests that low costs do not indicate a better (or worse) likelihood of preventing bank distress. Indeed, some of the distressed banks had very good cost-to-income ratios.

Liquidity does not come out significant in the baseline estimation. This is not very surprising, given that we are trying to identify distress over a one-year window. When a bank's problems turn into a liquidity problem, it is often only very shortly (i.e., days) before the

[16] Observations for individual banks may be correlated. To take this into account, we drop the standard assumption that errors are independent within each bank and use a variance-covariance matrix that is robust to clustering of errors.

failure (or intervention). Bank liquidity varies substantially over time, while our indicator accounts only for the amount of liquid assets banks hold in their portfolio at the last day of financial reporting. Unfortunately, bank balance sheets in BankScope are not available at a higher frequency. However, in the next section, as part of the robustness checks, we introduce another variable characterizing the liquidity exposure in a bank, namely the share of wholesale financing, and this variable does have a significant impact on the PD.

Despite its limitations, the baseline estimate fits the data rather well. This is illustrated for example by the pseudo *R*-squared, which is 0.48 for this baseline estimate (Table 3). This value compares favorably with similar models in the early warning system literature.

B. Robustness Checks

To assess the reliability of the baseline results, we employ a battery of robustness checks. Overall, the results (Table 3) are rather robust with respect to the sample selection, additional explanatory variables, and various changes in the estimation methodology.

We conduct a robustness check with respect to bank relevance/size. Given that our measure of bank distress is based on information collected from the search of databases of media reports, it is possible that a distress in a bank, especially a small one that is subject to relatively less scrutiny, may "fly under the radar" of the media. Bank failure is usually a very newsworthy item even if it occurs in a small bank, so it is unlikely that an outright bank failure would go completely undetected, also considering that the coverage of the database that we are using is extensive and includes specialized business media (Section III.B). Nonetheless, to check for this possibility, we delete from the sample all banks for which the NewsPlus/Factiva contains no information. These banks correspond to about one-third of the sample, and generally are indeed very small banks. The results of a reestimation without these "non-hitters" (Table 3 specification II) are very similar to the baseline model, both in terms of significance of the explanatory variables and in terms of the coefficient estimates. The model fit (pseudo *R*-squared) does not improve after this sample reduction, supporting the viability of using the total sample model as a baseline specification.

As a next step, we account for differences in macroeconomic environment among individual EU countries. Whether to expect macroeconomic variables to have a significant impact on bank PDs is not clear. The early warning models for bank supervision focus on the relative risk in individual banks and usually do not adjust for macroeconomic variables (Section III.B). But some macroeconomic variables are significant in studies on early warning models for systemic banking crises (see, e.g., Čihák and Schaeck 2007). For example, a higher inflation rate can be associated with a less stable macroeconomic environment and a relatively high likelihood of bank distress. Countries with a higher quality of supervision are likely to show less situations of bank distress, because problems in banks are prevented at an early stage (relatedly, Čihák and Tieman, 2006 and 2008, show that quality of supervision, in terms of compliance with good international supervisory practice, can be approximated by

GDP per capita). Finally, the financial deepening of the local economy can have implications in terms of financial stability. Countries experiencing surges in bank credit are found to be prone to systemic banking crises (Beck, Demirguc-Kunt, and Levine, 2006). On the other hand, the impact of these variables may be limited, given the EU's high degree of economic integration and the fact that many banks have operations in more than one EU country.

The results (specification III) suggest, perhaps surprisingly, that the variables capturing macroeconomic developments in individual countries do not have a significant impact on PDs in EU banks.[17] This seems to contradict the literature on systemic banking crises, where macroeconomic factors are usually found to play a significant role (Berg, Borensztein, and Pattillo, 2004). However, there are two important differences between that literature and our estimates, because we focus on (i) individual bank failures and (ii) relative macroeconomic performance in the EU countries. As regards (i), the impact of the macroeconomic environment is to some extent picked up by the "contagion dummy." This dummy has the value of one when another bank in the country was in distress in the last 12 months, which is more likely to occur in the case of adverse macroeconomic shocks that affect the whole country. Indeed, when we exclude the contagion dummy, the coefficients for inflation and for GDP become significant, while the rest of the estimate is basically unchanged.[18] This suggests that the macroeconomic factors do have some, even though a quantitatively small, impact on bank distress in individual countries.[19] As regards (ii), the low predictive power of the relative macroeconomic performance to some extent illustrates the high degree of economic integration within the EU and the fact that many of the banks have operations in more than one country, which limits the ability of country-level macroeconomic variables to explain individual bank distress.

Another check consists of controlling for common shocks (such as shocks to the euro-dollar exchange rate) affecting the EU countries. To allow for this possibility, we include time dummy variables in our estimations (specification IV). Most of the time dummy variables do not have a significant impact on bank distress (not shown to conserve the space), and the qualitative findings with respect to the main explanatory variables remain unchanged, supporting the robustness of our results.

We then control for the impact of repeated incidences of bank distress. Banks that have already experienced financial difficulties often struggle to improve their soundness and their reputation among customers. This results in repeated observations of distress in some

[17] To keep Table 3 legible, we show just the three macroeconomic factors discussed in the previous paragraph. We also tested the other macroeconomic variables that come out in the studies on systemic distress, such as Čihák and Schaeck (2007), and they were not significant. Results are available upon request.

[18] Results for this iteration of the robustness check are not shown in Table 3, but are available upon request.

[19] The intercept becomes insignificant when macroeconomic variables enter the specification, which may reflect a complex relationship between the contagion dummy, macroeconomic shocks and the baseline hazard.

banks.[20] When the repeated observations of distress are excluded (specification V), the results corroborate our findings for the baseline specification, suggesting that our main results are not driven by the repetitive distress events.

Next, we assess the impact of market concentration on the likelihood of bank distress. The theoretical literature provides ambiguous predictions in this respect. Some studies focus on bank liabilities and predict a negative relationship between market concentration and banks' risk of failure (Allen and Gale, 2004); others focus on the loan market and suggest a positive association between market concentration and banking risks (e.g., Boyd and De Nicoló, 2005). Introducing a concentration variable for individual countries (a Herfindahl index based on bank total assets) shows a positive and significant impact of market concentration on the PDs (VI). This suggests that more concentrated banking markets are characterized by a higher likelihood of bank distress. The impact of market concentration, however, becomes insignificant when macroeconomic variables are also entered in the model specification.

We evaluate the predictive power of the Z-score as a measure of the banking risk. The Z-score is calculated by summing the equity to assets and return on assets ratios and dividing the sum by the standard deviation of the return-on-asset ratio for the bank. The measure is designed to compare banks' buffers (capital and profits) with the risks they face (approximated by the standard deviation of returns). A higher Z-score should in principle mean a lower probability of insolvency. This interpretation, plus its simplicity, has made the Z-score a popular measure of bank soundness in the literature (for a survey of this literature, see, e.g., Čihák, 2007). When the Z-score is added to the model (column VII), the coefficient in front of the Z-score variable is insignificant, suggesting that the Z-score does not bring additional information on top of the baseline indicators for predicting bank PD.

We evaluate the extent to which stock market information may be helpful in predicting bank distress. This is a topic on which the literature is ambiguous. For the U.S. banks, most of the literature finds evidence that stock market indicators have a useful predictive content for identifying financial distress (e.g., Flannery, 1998; and Curry, Elmer, and Fissel, 2003). The literature for other countries is generally less conclusive (e.g., Bongini, Laeven, and Majnoni, 2002), and even for the United States, there is some evidence on the weakness of market prices in predicting bank failures (Gilbert, 2002). To perform this robustness check, we use information on stock prices for 222 EU banks, and calculate ratios of stock indices relative to the FTSE-100 (Financial Times Stock Exchange) market index.[21] A plausible hypothesis is

[20] There are 21 repetitive distress bank-year observations in total. The remaining 54 distress events correspond to the number of distressed banks in the sample.

[21] Listed banks were identified from BankScope by their International Securities Identification Number (ISIN). Daily series of bank stock prices and the FTSE-100 index are taken from Datastream. The market information variable takes a value of 0 for the nonlisted banks. Because the logit estimate is based on annual data, we use yearly averages of the daily stock price data. We also experimented with different approaches to mapping the daily data into yearly data, but this had little impact on the results.

that, if a bank stock deviates substantially from the general stock market trend in one year, it stands for a correction in the next year, and this correction can expose the banks' weakness. The argument behind this reasoning is that fast expansion is often overvalued by the stock market and leads to an accumulation of bad loans when lending standards are lax. The estimation results (specification VIII) are consistent with this hypothesis, as the estimated coefficient is positive and significant, suggesting a positive association between deviations from stock market trends and bank PD in the next period.

To explore the effect of wholesale financing on the likelihood of bank distress, the share of wholesale financing in bank total liabilities was included as an additional explanatory variable. Wholesale funding is usually not a part of the traditional deposit protection schemes. This makes wholesale lenders more jittery in the event of financial turbulence, and banks in turn more vulnerable to sudden withdrawals. Recent evidence (e.g., in the case of Northern Rock) provides examples of runs by retail depositors preceded by a run by wholesale lenders. The results of this analysis (IX) confirm that banks relying more heavily on wholesale financing are more likely to experience financial distress than those banks that are mostly financed by retail depositors.

To examine robustness of the results with respect to the estimation method, two types of random effects models are estimated: one in which the intercept varies at the individual bank level (column X) and one in which the intercept varies at the country level (column XI). Model (X) exploits the heterogeneity of the baseline hazard (the probability of bank distress after accounting for its financial characteristics) at the individual bank level, while the latter model exploits the baseline hazard heterogeneity at the country level. The estimate of the standard deviation is significant in model (X), implying remaining heterogeneity across banks due to the bank-specific characteristics not captured by the explanatory variables X_{ijt-1}. However, the standard deviation of the random intercept is insignificant at the country level in specification (XI), implying that the EU countries are relatively homogenous in terms of the bank baseline hazard after accounting for a set of financial ratios X_{ijt-1}. Both panel data specifications (X) and (XI) produce qualitatively similar results for the key financial indicators compared with the pooled specification (I), suggesting that the main difference comes from the heterogeneity of intercepts, rather than the heterogeneity of slope coefficients. These findings lend support for establishing common benchmark criteria for banking sectors across the EU countries.

Given the dominance of German banks among the distressed banking institutions in the EU, we run a separate estimation of the baseline model by excluding Germany from the sample. Estimation results (column XII) show that our main results (except from the impact of asset quality) are valid even when German banks are not considered as a part of the sample.

To check the robustness of the results with respect to the organizational form of banks, we reestimate the baseline specification for only commercial banks, which account for about half of the observations of bank distress (39 out of 79), the rest pertaining to savings banks, cooperative banks, specialized governmental institutions, bank holding companies, investment banks, and real estate banks. The estimation results (XIII) suggest that our findings are applicable also to commercial banks separately, as all qualitative findings (except for the impact of banking capitalization) remain unchanged.

To test whether the failures in the recent crisis are fundamentally different from the earlier failures, we reestimated the model only for those 19 failures that occurred in 2008, that is, we ran a cross section estimate based on 2007 data, predicting the 2008 failures. The estimate (XIV) performs well in terms of the pseudo R-squared and predictive power (15 failures out of 19 are identified for a cutoff point at PD=1 percent). Compared with the baseline estimate based on the full 1995–2007 sample, this estimate suggests that capitalization has a significant impact on PDs, and that managerial quality (insignificant in the baseline estimate) may play a role. At the same time, asset quality, significant for the full sample, is not significant in this reduced sample. The other variables, specifically the contagion dummy, the market discipline variable (the deposit rates), and the market information variable (the stock prices) have the same significance and similar values to the baseline estimate. This suggests that, even though the 2008 distress was different from anything seen in the recent past, some mechanics identified in the longer panel data remained in place even in the recent crisis.

We also experimented with the time horizon in the model. In all the regressions so far, the default lag for all explanatory variables was one year. As a robustness check, we used explanatory variables lagged by two and three years. These checks yielded similar results to the benchmark (and are available upon request), but were weaker in terms of significance, suggesting that the predictive power of the explanatory variables declines as one attempts to predict failures farther into the future.[22]

The final pair of robustness checks focused on the definition of contagion. Instead of defining similarity among banks as asset size within EUR ±200 million) we (i) defined "similar size" as EUR ±100 million and (ii) we explored using the share of loans to total assets, with a ±5 percent band, as an alternative measure of similarity. The estimation results do not change substantially (the results are available upon request).

The bottom line of all these robustness checks is that the baseline model performs reasonably well. The main advantage of this model is that it is relatively parsimonious: it uses easy-to-calculate variables that are helpful in predicting actual distress events. The predictive power of these indicators does not change much when other potentially relevant control variables are included or when different estimation methodologies are used.

[22] We also experimented with shortening the lag of the stock market prices below one year in estimate (VIII), using the high frequency with which stock market data are available. This allows us to further improve the predictive power of the model, but the weakness of this approach is that it would not provide a sufficiently early warning; moreover, reliable stock price data are available only for a minority of the banks in our sample.

Table 3. Logit Estimation Results

Models	(I) Baseline	(II) Excluding non-hitters	(III) With macro variables	(IV) With time effects	(V) Only first distress	(VI) With market concentration	(VII) With Z-score
Capitalization	-26.578**	-25.085**	-17.449	-22.166**	-21.218**	-28.551**	-14.820**
Asset quality	20.443**	18.737**	19.426**	16.725**	14.875**	18.950**	2.339
Managerial quality	-0.109	-0.105	0.061	-0.102*	0.000	-0.107	-0.313*
Earnings	-1.911***	-1.790**	-1.653**	-2.324***	-1.101**	-2.377***	-6.099***
Liquidity	-0.405	-0.526	0.157	-0.316	-0.351	-0.246	-0.348
Market discipline	4.957***	5.082***	3.885***	4.446***	5.057***	4.649***	4.000***
Contagion dummy	6.072***	5.829***	6.834***	7.041***	6.011***	5.956***	5.798***
Inflation			0				
Per capita GDP (logs)			0.129				
Share of domestic credit in GDP (logs)			-0.496				
Concentration (Herfindahl)						5.136**	
Z-score							-203.95
Market information							
Wholesale liabilities (share)							
Intercept	-5.494***	-5.173***	-6.068	-3.427***	-6.285***	-5.709***	-4.756***
Number of observations	29,862	18,164	29,155	29,862	29,837	29,862	29,417
Pseudo R-squared	0.480	0.469	0.613	0.551	0.462	0.490	0.497
Log likelihood	-284.6	-270.2	-166.7	-245.8	-212.5	-279.3	-257.0
Random error (log of st. dev.)	--	--	--	--	--	--	--

Models	(VIII) With stock prices	(IX) With wholesale financing	(X) RE banks	(XI) RE countries	(XII) Excluding Germany	(XIII) Only commercial banks	(XIV) Only 2008 distress
Capitalization	-27.466**	-30.268**	-37.059***	-29.239***	-26.259***	-13.008	-44.490***
Asset quality	20.609**	18.187**	29.513***	19.368**	10.054	16.567**	-67.735
Managerial quality	-0.110	0.049	-0.119	-0.121*	0.192	0.035	-0.184**
Earnings	-1.957***	-1.868**	-2.360**	-2.125***	-0.698**	-1.204**	-4.357***
Liquidity	-0.413	-0.264	-0.886	-0.6	-1.099	-1.627*	-0.614**
Market discipline	4.974***	4.932***	7.724***	5.082***	4.476***	4.115***	5.182***
Contagion dummy	6.086***	6.348***	8.756***	6.388***	5.750***	4.809***	3.377***
Inflation							
Per capita GDP (logs)							
Share of domestic credit in GDP (logs)							
Concentration (Herfindahl)							
Z-score							
Market information	4.965***						5.341***
Wholesale liabilities (share)		0.163***					
Intercept	-5.469***	-5.809***	-8.862***	-5.423***	-7.447***	-5.269***	-2.149***
Number of observations	29,862	27,800	29,862	29,862	13,924	7,556	4,358
Pseudo R-squared	0.485	0.506	0.487	0.520	0.516	0.443	0.337
Log likelihood	-282.3	-211.6	-247.8	-282.1	-138.3	-136.0	-112167.0
Random error (log of st. dev.)	--	--	2.077***	-0.263	--	--	--

Notes: *, **, and *** indicate significance at 10, 5, and 1 percent levels, respectively. R-squared for the random effects (RE) model is calculated using McFadden's likelihood ratio.

C. Prediction Results

An important property of the logistic model is its precision in terms of minimizing Type I and Type II errors. A Type I error occurs when the model fails to identify the distressed bank, and a Type II error occurs when a healthy bank is falsely identified as distressed. To attribute a particular bank into one of the two categories (distressed versus healthy), one needs to set up a cutoff point in terms of the bank PD. All banks above that cutoff point are blacklisted as weak banks, while all banks below that point are classified as healthy.

A higher cutoff point results in a lower number of banks on the blacklist of weak banks, which tends to increase the Type I errors. Setting a lower cutoff point can reduce the Type I errors, but at the expense of generating more Type II errors. The optimal cutoff point depends on the relative weights that an analyst puts on Type I and Type II errors. Some of the available literature simply adds Type I and Type II errors; however, from a prudential perspective, there is a case for putting a larger weight on Type I errors (e.g., Persons, 1999), because supervisors are primarily concerned about missing a distressed bank. This implies a preference for relatively low cutoff points, which limit the Type I errors at the expense of relatively long blacklists (and potentially more Type II errors). To address the trade-off between Type I and Type II errors, we illustrate the sensitivity of Type I and Type II errors with respect to the choice of the cutoff point.

Table 4 displays the relationship between model predictions and actual distress events for our baseline specification using three different cutoff points (10, 1, and 0.5 percent). The table shows that the model correctly classifies 44 out of 79 distress events (55.7 percent), and 29,706 out of 29,783 nondistress events (99.7 percent) for the 10 percent cutoff point. The model failed to correctly classify 35 distress events out of 79 (Type I error) and wrongly classified 77 healthy bank year observations out of 29,783 as distressed (Type II error). Overall, the model performs satisfactorily in classifying distressed banks.

Table 4. Type I and Type II Errors

Cutoff point: PD = 10 percent		Actual distress		
		Yes	No	Total
Classified distress	Yes	44	77	121
	No	35	29,706	29,741
	Total	79	29,783	29,862

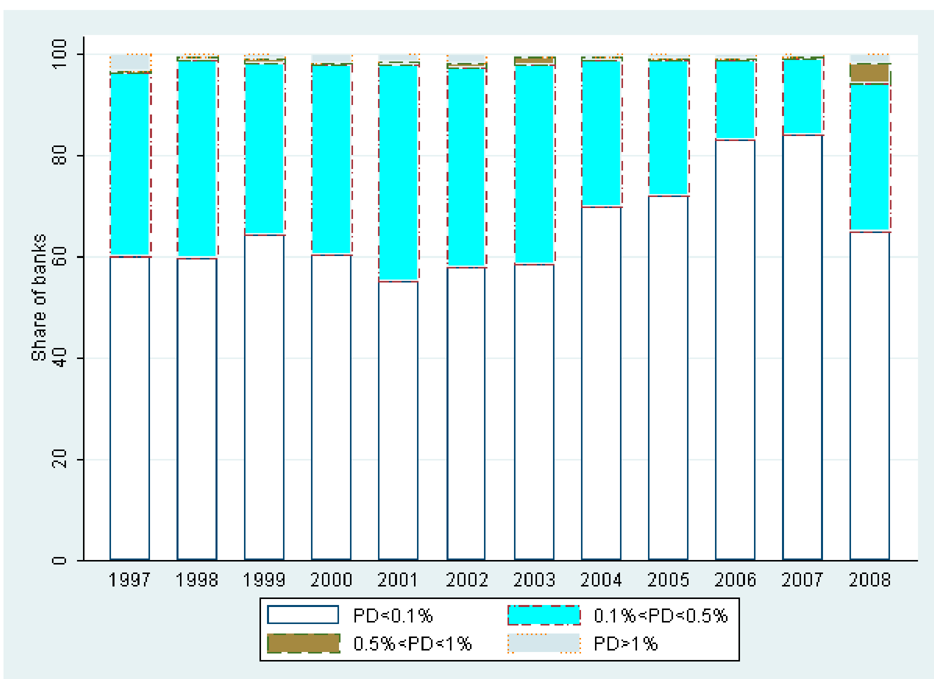
Cutoff point: PD = 1 percent		Actual distress		
		Yes	No	Total
Classified distress	Yes	50	258	308
	No	29	29,525	29,554
	Total	79	29,783	29,862

Cutoff point: PD = 0.5 percent		Actual distress		
		Yes	No	Total
Classified distress	Yes	54	417	471
	No	25	29,366	29,391
	Total	79	29,783	29,862

Lowering the cutoff point to 1 percent results in a slight decrease in the number of Type I errors (the number of correctly classified distress events goes up to 50). However, this coincides with a substantial increase in the number of the Type II errors: the number of incorrectly classified distressed banks goes up from 77 to 258. Decreasing the cutoff point further to 0.5 percent results in an even larger increase in the number of the Type II errors, while leaving Type I errors basically unchanged. In the absence of a substantial reduction in Type I errors, a case could be made for adopting the 10 percent cutoff point.

Figures 2 and 3 illustrate the distribution of banks in terms of the predicted PDs. Figure 2 shows the simple distribution of the PDs across banks without weighting them, while in Figure 3, the banks are weighted by their assets. The share of total bank assets at high level of risk (PD>1 percent) grew steadily from 1997 to 2004. At the end of the sample, the share of total assets at high level of risk went down. An opposite picture emerges for the assets subject to a relatively lower risk (PD<0.1 percent), with their share rising at the end of the sample. The distribution of the number of banks as a share of the total number, based on their risk characteristics, suggests that the majority of the banks belong to the lowest category of risk (PD<0.1 percent). However, a comparison with Figure 3 highlights the uneven distribution of banks and their assets, suggesting that the economic impact of banks' risk can be high when weighted by the volume of bank assets.

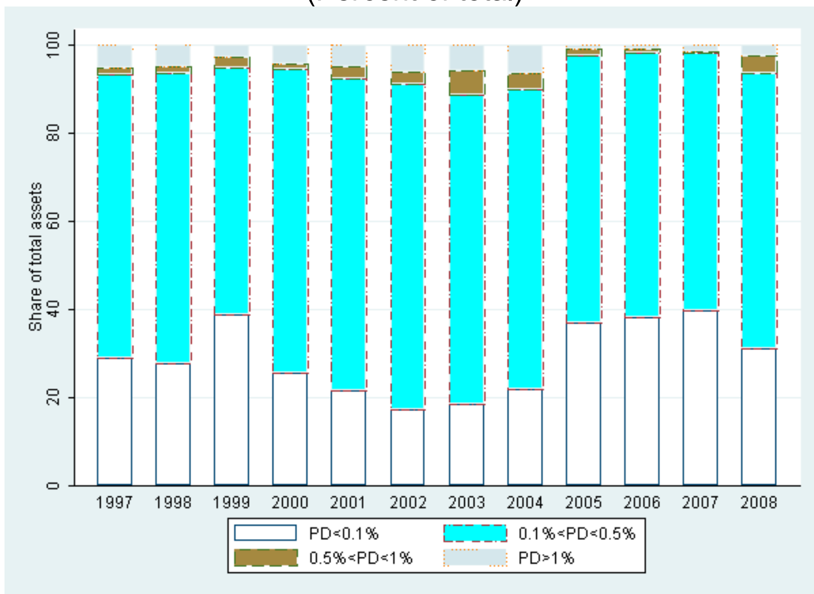
Figure 2. Banks at Risk
(Percent of total)



Source: Authors' calculations.

Figure 3. Assets at Risk

(Percent of total)



Source: Authors' calculations.

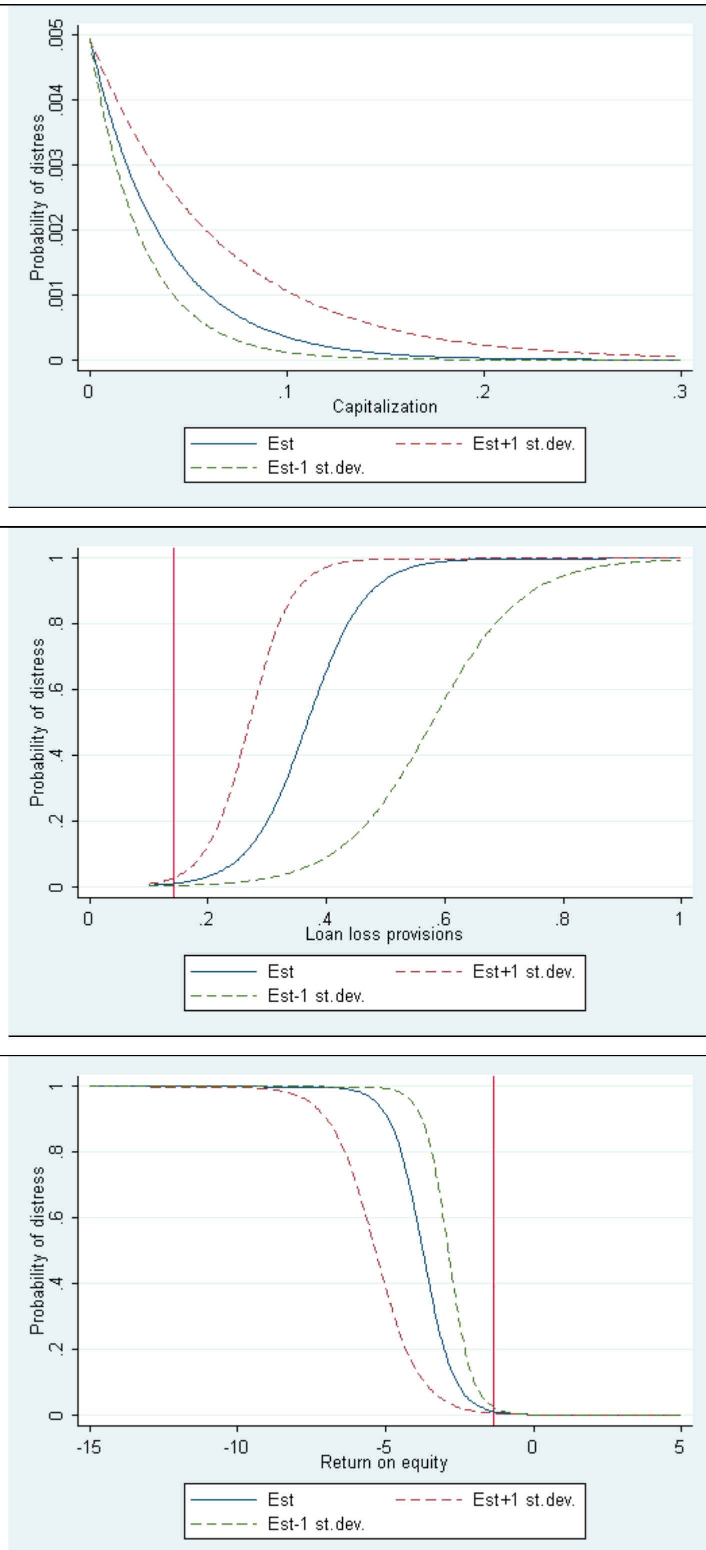
D. Marginal Effects

The coefficients of the logit model have a nonlinear impact on the probability of bank distress. The magnitude of the impact depends on the initial values of independent variables and their coefficients. Therefore, to evaluate the marginal impact of individual financial ratios, Figure 4 presents the estimates of the marginal impact computed at the sample mean. The figure focuses on the marginal impacts of the three CAMEL covariates that were found to have a significant impact on bank PD: capitalization, asset quality, and earnings.

Eyeballing Figure 4 allows us to identify the trigger points in the levels of these three covariates that result in an increase of bank PD above a given cutoff point. For example, if we choose the 10 percent cutoff point in terms of PDs (discussed in the previous sub-section), the middle part of Figure 4 suggests that, for asset quality, this corresponds to a trigger point of 14.3 percent of loan loss provisions relative to bank loans (assuming the other covariates are at the sample means).

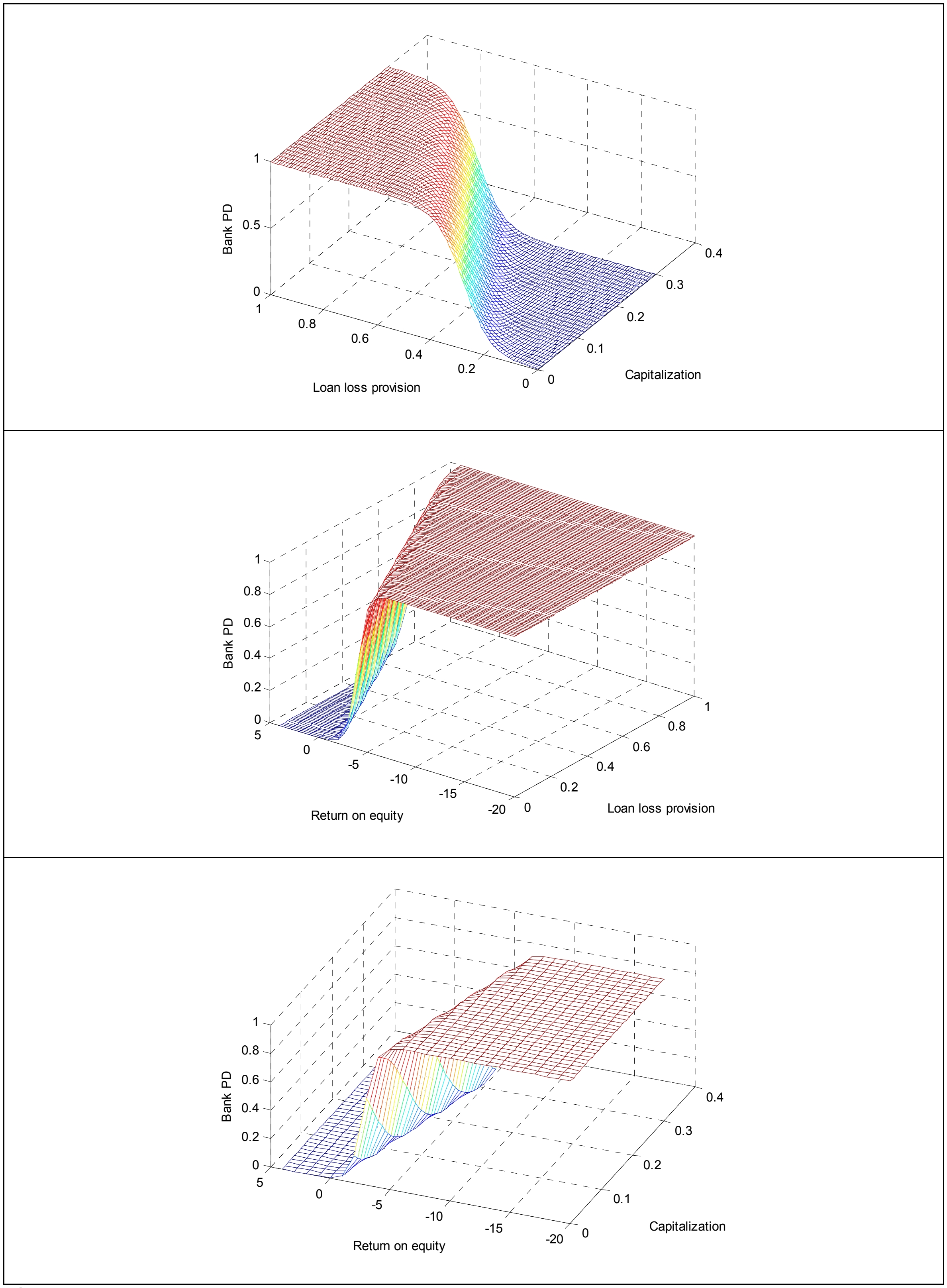
Figure 5 shows the marginal impact of different pair combinations of significant CAMEL covariates in a three-dimensional space. Specifically, the two axes on the horizontal plane show capitalization and loan loss provisioning, and the vertical axis shows the PDs. The figure illustrates the trade-off between the two covariates: if a bank's loan loss provisioning increases, its PD will remain unchanged if it increases its capitalization accordingly. Similar trade-offs exist for the other pairs of PD determinants: loan loss provisioning versus ROE, and ROE versus capitalization.

Figure 4. Marginal Effects of Significant CAMEL Covariates



Source: Authors' calculations.

Figure 5. Trade-off in the Impact on PD Between Pairs of Significant CAMEL Covariates



Source: Authors' calculations.

V. Conclusion

We present a new, comprehensive database of past instances of distress in EU banks, and analyze this database to estimate an EU-wide early warning system for bank distress.

The main finding of the paper is that based on a rigorous analysis of past instances of bank distress, it is possible to establish plausible thresholds for identifying weak banks. The thresholds can be mapped into the CAMEL covariates, notably capitalization, asset quality and profitability. In contrast, cost-to-income ratios and basic liquidity indicators do not seem to have a good predictive power. Instead, a liquidity indicator that captures the share of wholesale financing in liabilities contains useful information about PDs.

We find that depositor discipline has an important signaling effect: when a bank pays more on deposits than its competitors, it has a significantly increased probability of distress. Contagion effects play an important role as well: the probability of distress in a bank is significantly higher if there was a recent distress in a bank of a comparable size in the same country.

We find that stock prices, when available, contain useful information about the likelihood of a bank's default. In contrast, accounting measures such as the Z-score, do not seem to contain information additional to what is already in the CAMEL indicators.

We also find that more concentrated banking markets are characterized by a relatively higher likelihood of bank distress. Differences in the macroeconomic environment among the EU countries play some, but a relatively small, role in predicting individual bank PDs. This does not mean that the macroeconomic environment is irrelevant; rather, it reflects the relatively high degree of economic and financial integration within the EU.

An important finding is that EU countries are relatively homogenous in terms of the bank baseline hazard, after taking into account the various explanatory variables. Also, the estimated slope coefficients do not show much heterogeneity across countries. These findings lend support for establishing common benchmark criteria for banking sectors across the EU countries, and potentially also for the proposition of a common EU supervisory framework.

The estimated early warning system provides a set of criteria for bank soundness. Such criteria could be useful for bank depositors and other creditors. Policymakers could use them to limit the scope for supervisory forbearance and set up a more rules-based framework for supervision across the EU: if a bank would exceed certain trigger points, it would become subject to closer scrutiny, and potentially become subject to supervisory intervention. Of course, this early warning system will have to be used wisely, because a purely mechanical application could allow banks to bypass the framework through creative accounting or other types of misreporting. Also, the early warning system cannot be cast in stone forever. It needs to, as suggested in a different context by King, Nuxoll, and Yeager (2006), be reestimated and reassessed to respond to new developments the system—a point particularly relevant in today's European banking market.

Further work in this area would benefit from the creation of a unified database of supervisory data in the EU. Country supervisors have access to more detailed indicators than what is publicly available (e.g., bank exposures to individual sectors and various breakdowns of data by maturity, currency, and performance). Such information, which is currently unavailable in a single database for the EU, could be used to improve on the early warning system designed in this paper.

APPENDIX I. EARLY WARNING SYSTEMS FOR BANKING SUPERVISION: SURVEY

Financial ratio and peer group analysis systems

It is broadly acknowledged that banks' financial condition can be related to a fairly consistent set of financial variables, which include measures of capital adequacy, asset quality, profitability and liquidity (e.g., Sahajwala and Van den Bergh, 2000; and King, Nuxoll, and Yeager, 2006). The financial ratio analysis generates a warning if a ratio exceeds a predetermined critical level, lies within a set interval, or is an outlier as far as the past performance of the bank is concerned. Peer group analysis is undertaken on the basis of financial ratios for a group of banks taken together. This is used to ascertain whether an individual bank is performing in a significantly different way from its peers and the reason for such significant difference, which may or may not imply supervisory concern.

The peer groups are usually based on asset size (e.g., small versus large banks) or specialization (e.g., domestic commercial banks, foreign banks, cooperative banks, or savings banks). Each bank's individual ratios are compared with its peer group. Within each peer group, either a simple identification of the worst performers compared with the peer average is made or the financial ratios are sorted from best to worst, and percentile rankings are calculated. Individual banks whose financial ratios have deteriorated relative to the averages of their respective peer group can then be identified.

Statistical model*s*

Some supervisory authorities make use of formally estimated statistical supervisory models. Such models have been used for example by the Federal Reserve, the FDIC, and the Office of the Comptroller of the Currency (OCC) in the United States, the Financial Services Authority in the United Kingdom, the French Banking Commission, the Deutsche Bundesbank in Germany, and the Bank of Italy. The available methodologies can be broadly classified as follows: (i) models estimating ratings or rating downgrades, (ii) failure or survival prediction models, and (iii) expected loss models.

Models estimating ratings or rating downgrades

An example of this type of model is the System for Estimating Examination Ratings (SEER) model used by the U.S. Federal Reserve (since 1993). The model employs a multinomial logistic regression to estimate a bank's probable CAMEL composite rating on the basis of the most recent call report data. Specifically, it estimates the probability that the bank's next composite CAMEL rating will be each of the five possible ratings (1–5). The SEER rating is the sum of the five rating levels multiplied by their respective probabilities.

The model first determines the historical relationship between call report data and examination ratings by using call report data from two previous quarters and the corresponding latest examination data. The relationship between the dependent (examination rating) and explanatory variables (from call reports) as estimated during this period is then used to estimate events during a subsequent period. The model provides a statistical relationship between the latest composite CAMEL on-site rating and a list of about 45 financial and nonfinancial variables. Variables that are not statistically significant in predicting the composite CAMEL rating for the current quarter are eliminated from the model. Variables used in the model include past-due loans, nonaccrual loans, foreclosed real estate loans, tangible capital, net income, investment securities, an asset growth variable, prior management rating, and the previous composite CAMEL rating. The model combines the weights of the selected variables with the current value of those variables from call reports for each bank to estimate the probable composite CAMEL ratings for the respective institution. If the estimate is significantly different from the most recent on-site examination rating, the bank is singled out for further review.

Models predicting failure or survival rates

These models are estimated on a sample of failed or troubled banks, tested on another hold-out sample of failed or distressed banks for estimation accuracy, and then used out of sample to identify banks whose ratios or indicators most resemble those estimated in the models. To continue in the example from the previous section, the U.S. Federal Reserve also uses a version of the SEER model that estimates the probability that a bank will become "critically undercapitalized" during the subsequent two years. The estimation is based on a bank's financial condition as measured on the basis of the most recent call report data. The model employs a bivariate probit regression to estimate the probability of failure. The model makes use of the characteristics of bank failures in the United States during the period 1985–91 to provide a statistical relationship between bank failures and financial information. Being based on call report data as the input data, the model is run every quarter. When the model was initially developed, the estimation period for the model changed every quarter, as it used two prior years as the estimation period to calculate the variable weights. However, as the number of bank failures decreased throughout the 1990s, a model was developed on the basis of pooled cross-section and time-series data for the period 1985–91. The model makes use of 11 explanatory variables, the individual bank values of which are used to calculate risk rank. The model automatically flags banks with a risk rank higher than a predetermined threshold for more intensive review by Federal Reserve Bank analysts.

The output of the model, which was initially a simple listing of the variables that contributed to a bank failing the risk rank criteria, was updated in 1997 to include a detailed "risk profile analysis" that includes a "peer analysis" and a "change analysis" for each bank. The former reports information about the risk of a bank relative to its peers, and the latter provides information about the factors responsible for the changes in a bank's risk rank over time. The distribution of risk ranks across banks and its average also provides measures of the current level of risk in the banking industry based on financial information reported in the call reports.

In Germany, the Deutsche Bundesbank uses a hazard rate model to model developments in the soundness of German savings and cooperative banks. The model uses a range of indicators to estimate the probability of an institution's existence being endangered within a period of one year without support from the institution's affiliated network. The determinants are based on the CAMEL ratings and reflect the capital adequacy, profitability, credit risk, and market risk of each savings bank or credit cooperative. These are supplemented by regional and macroeconomic factors (Deutsche Bundesbank, 2004).

Some agencies (e.g., the Bank of Italy and Bundesbank) have been employing the duration model. The duration model generates estimates not only of the probability of failure of a bank, but also of the probable time to failure. In such a model, which assumes that every bank will ultimately fail, the dependent variable is not just failure but time to failure. The model constructs an equation that allows calculation of the probability that a bank with certain specific characteristics will survive longer than some specified time into the future, or fail at a specified time in future, where the time can vary over a range of values.

Expected loss models

Countries that do not have a history of bank failures or have had only infrequent failures may find it difficult to estimate a failure or survival prediction model, as there would not be enough statistical evidence to link financial variables to failure. In such a situation alternatives include having a modulated definition of failure, as is done by Bank of Italy in its early warning model, or trying to predict the future solvency of a banking institution by estimating potential future losses, as is done by the French Banking Commission.

The French Banking Commission's Support System for Banking Analysis (SAABA) model has been in use since 1997. The model is based on the premise that credit risk is the major risk faced by banks. The final diagnosis includes qualitative assessments relating to ownership and shareholder quality, as well as management and internal controls. The input data and information come from the Banking Commission's own databases, the Bank of France database, and external sources. The methodology of the model involves adjusting all outstanding individual and corporate loans of a banking institution with a potential future loss amount. The potential loss amount is based on the default probability worked out in the case of each individual credit on the basis of available data and information. Individual potential losses are summed to arrive at a total for the entire credit portfolio over a three-year period. This total potential loss figure is then adjusted against the current level of reserves. The unadjusted balance represents the potential future loss, which is deducted from the current level of the bank's own funds. If the bank's own funds fall below the 8 percent requirement after the quantitative analysis, the bank's future solvency is questionable. SAABA complements the quantitative diagnosis with an assessment of shareholders' ability to support the banking institution, and of management, internal controls, and liquidity of the institution.

Issues

Statistical early warning models are based on rigorous quantitative analysis. As such, the impact of qualitative factors such as management quality, internal control, and other bank-specific factors is not typically represented in the models. It is widely acknowledged that these qualitative factors, particularly the efficiency or inefficiency of management, can also be significant causes of bank failure. However, few models attempt to quantify management quality or incorporate realistic surrogates for management performance. The models are also not designed to capture the risk of failure on account of other nonfinancial factors like fraud or financial misconduct.

Since statistical models are new and their output is generally supplemented with those from other systems in identifying problem banks, supervisory authorities continue to use and fine-tune the models despite the outcomes of the error rate trade-offs. The early warning models in use are subject to some form of back testing and validation studies. The Federal Reserve reportedly undertakes an annual validation study for the SEER rating and risk rank models, which compares the predictions made by the models with the actual examination rating or event. The composite rating estimated by the SEER rating model is compared with the actual rating assigned by the examiner to determine that model's performance. To evaluate the predictive ability of the SEER risk rank model, the number of estimated failures (survivors) is compared with the number of actual failures (survivors) and the Type I and Type II error rates are computed. Similarly, the French Banking Commission reports that periodic back testing is carried out to ascertain whether the model correctly identifies banks that are likely to run into serious problems. To test the efficacy of its model, the FDIC compares the composite scores from the model with future bank failure rates. The analysis shows that banks in the lowest composite score decile usually fail at the highest rate during the two years immediately after the scores were measured and those in the highest decile fail at the highest rate between three and five years after the scores are assigned.

Statistical models currently in use are mainly unconditional models. The models predict that a bank is likely to fail or that its condition will deteriorate given the current value of the independent variables. They do not condition the forecast on assumptions about the future path of any of the variables included in the model. Some supervisory authorities have been attempting to develop models based on forecasts of individual bank variables and the resultant failure or survival probability. While some of the early warning models have achieved satisfactory results, these have been achieved in limited contexts. Accurately predicting the probability of a rating downgrade, probability of failure or survival, expected losses or insolvency, over a wide range of institutions and time periods proved to be difficult.

APPENDIX II. EUROPEAN BANKING SYSTEM

The European Union has a developed banking system with approximately 8,000 banks. Within this group, large cross-border banks have emerged, which have a substantial market share. European banking integration is gaining momentum in terms of cross-border flows, market share of foreign banks in several domestic markets, and cross-border mergers and acquisitions of significant size (e.g., Schoenmaker and Oosterloo, 2007). A rapidly growing number of LCFI engage significantly in cross-border business. The bulk of this business is in wholesale markets, which are now relatively well integrated, notably interbank and corporate bond markets (in contrast, there is considerable scope for further integration in equity, securitization markets, and arms' length financing). A mapping exercise of EU banking groups with significant cross-border activity carried out by the Banking Supervision Committee of the European System of Central Banks revealed that some 46 LCFIs hold about 68 percent of EU banking assets; of these, 16 key cross-border players account for about one-third of EU banking assets, hold an average of 38 percent of their EU banking assets outside their home countries, and operate in just under half of the other EU countries (see, e.g., ECB, 2005 and 2006). The legal, regulatory, and supervisory framework has not been able to keep up with this rapidly growing cross-border presence, notably the centralization of treasury and risk management functions of the LCFIs.

The IMF has been arguing that the EU needs a more integrated approach to financial stability (e.g., IMF, 2007).[23] This fact has been highlighted by the ongoing global financial crisis. Since the Treaty of Rome in 1957, the EU has sought to establish a single financial market. It has made major progress toward this objective, but completing the process and managing the related risks require an integrated approach to financial stability[24].Political preference as well as legal and institutional considerations have thus far limited the progress on cross-border financial stability arrangements.

The fundamental problem is that national supervisors' fiduciary responsibilities are toward national governments and parliaments. This limits their incentives to work toward common EU objectives. IMF staff has for some time argued that the EU needs joint responsibility and accountability for financial stability, and that this should be underpinned by more complete information sharing (also with the ECB) and better crisis prevention, management, and resolution frameworks.

The EU has adopted a set of cross-border crisis management principles and a supporting Memorandum of Understanding (MoU). These principles, adopted by the October 2007 ECOFIN, commit member states to act in crises to minimize the "potential harmful economic

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[23] See also De Haan, Oosterloo, and Schoenmaker (2009) for an extensive discussion of the European financial stability framework.

[24] See Decressin, Faruqee, and Fonteyne (2007).

impacts at the lowest overall collective costs." If public resources are needed to achieve a cost-minimizing solution, then direct budgetary net costs are to be "shared among Member States on the basis of equitable and balanced criteria." The recently agreed MoU seeks to implement these principles. It commits member states to putting in place national and cross-border arrangements to manage financial stability problems, a set of common guidelines for crisis management, and a common assessment framework to determine the systemic nature of a crisis. Meanwhile, work is ongoing to overhaul the legal framework to deal with solvency problems in cross-border banks, covering inter alia improvements to deposit guarantee schemes, a framework for early intervention and reorganization measures, and an assessment of obstacles to cross-border asset transferability.

The Lamfalussy framework, aimed at achieving regulatory and supervisory convergence, is being reinforced. The framework was set up to facilitate financial sector rule making at the EU level and achieve a more consistent application of these rules at the national level. The so-called Level 3 Committees of this framework bring together national supervisors and have been tasked with much of the burden of achieving the desired convergence. The December 2007 ECOFIN launched a roadmap of reforms to reinforce these committees by giving them more resources, introducing scope for qualified majority voting, and strengthening the national application of guidelines issued by these committees, while keeping the nonbinding nature of the guidelines.

The crisis management principles have introduced recognition of a collective responsibility and a need to share costs. However, in a severe crisis, national interests may still prevail over the good intentions embedded in these principles and the nonbinding MoU. The MoU also risks further adding complexity to the cross-border financial stability setup. All in all, timely and collective cost minimizing solutions may still prove out of reach. The key challenge is to align the legal underpinnings of nationally-anchored financial stability frameworks and the incentives of the relevant agents with the commonly agreed principles.

APPENDIX III. EUROPEAN STRUCTURED EARLY INTERVENTION AND RESOLUTION

Prompt intervention is needed to achieve efficiency and cost minimization in bank resolution. Schemes that prescribe mandatory action at certain trigger points are referred to as "structured early intervention and resolution" (SEIR) or "prompt corrective action," the latter being a more specific form of the former, focusing on liquidation (Nieto, Mayes, and Wall, 2008). A SEIR framework for cross-border systemic banks in the EU would need to aim at preventing failures and restoring failed banks to health. The following principles for efficient resolution procedures can be identified (e.g., Eisenbeis and Kaufman, 2005):

- The prudential authorities need to act as soon as a solvency shortfall or other warning signals are detected. If the solvency shortfall is not large, the bank should initially be given a grace period to restore its solvency to the regulatory minimum, albeit under intensified supervision and restrictions on its actions.

- If there is no improvement after the grace period, a capital injection should be imposed. In the absence of controlling shareholders or in case they are unable to mobilize new capital, shareholders would have to accept a dilution of their ownership stake.

- If no private sector solution has been found and solvency drops below a certain level or another trigger point is met, there should be a mandatory and prompt suspension of shareholder rights, a bank resolution agency should take custody or receivership of the bank, and new management should be put in place.

- In custody or receivership, the bank resolution agency needs to make a quick early assessment so as to allow continuity in the bank's core operations and minimal or no disruption in the availability of most deposits. If the bank's estimated solvency is negative, some liabilities could be blocked or separated from the (bridge) bank pending a more complete audit and the final determination of losses.

- Systemic and core operations of the bank, including basic retail services, should continue uninterrupted or after a minimal interruption not exceeding one or two days. The continuation could be assured by a new entity (a bridge bank).

- The reopened bank should be recapitalized, restructured, and prepared for sale, as a whole or in parts, to private acquirers within a relatively short time period. The proceeds from the sale, net of any recapitalization and management costs, should be used to pay off liabilities that have not been assumed by the reopened bank, according to their legal priority. Any funds remaining at the end of the resolution process should be disbursed to the bank's original shareholders.

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