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Distress in European Banks: An Analysis Based on a New Dataset

Tigran Poghosyan and Martin Čihák

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Distress in European Banks: An Analysis Based on a New Dataset

Prepared by Tigran Poghosyan and Martin Čihák[1]

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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 European Union (EU) from mid-1990s to 2008. Using this dataset, we analyze suitable "benchmarks" of good banking performance in the EU. 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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Contents Page

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 publicly available on 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 dataset 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. The literature, however, says little about predicting failures in EU banks. This most likely reflects the fact that the number of bank failures in EU countries has so far been relatively low (at least until recently). In fact, some EU countries had no bank failures in the last several decades. 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, in recent months, we have witnessed some high-profile cases of bank distress, which have provided fresh observations for the database.

Based on this database, and using an extensive panel data on individual EU banks (both those that have and those that have not experienced distress), we analyze suitable "benchmarks" of good banking performance 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 in more detail on that institution, and if questions about soundness of that institution persist, to enforce a corrective action and in an extreme case even step into a bank to take it over early enough, before its capital is entirely depleted.

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 still country-by-country based supervisory arrangement. An EU-level early warning system based on a model of this kind could provide a useful "benchmark" for good banking performance. 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, allowing country-level supervisory discretion and forbearance, towards a system that is more rules-based and more uniform across the EU.[2] Such a framework would be in line with the EU authorities' stated goal of promoting European financial integration.

Our paper lends empirical support for the proposition of establishing EU-wide benchmark criteria for banking sector performance. 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 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 early intervention systems. Section III explains the estimation methodology and the data being used. Section IV presents the estimation results. Section V concludes.

II. MOTIVATION

A. Early Warning Systems for Banking Soundness[3]

A survey of the relevant literature suggests that leading indicators of bank distress can be grouped into three main categories. The first category are standard balance-sheet and income statement financial ratios. This includes the so-called CAMELS variables (where CAMELS stands for "capital, asset quality, management, earnings, liquidity, and sensitivity to market risk"). These variables are very popular in the "supervisory risk assessment and early warning systems" 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 medium- to long-term horizon. In the short run, profitability, liquidity and solvency indicators provide helpful information on banks' financial condition (see Appendix I for details).

There is a relatively broad agreement in the literature and among the practitioners that the CAMELS indicators are useful in grading banks in terms of their financial vulnerability, and

[2] 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.

[3] 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).

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 CAMELS components 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 CAMELS 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 are 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 CAMELS indicators (e.g., Flannery, 1998; Curry, Elmer, and Fissel, 2001).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 are other, somewhat less common, measures of bank risk and financial strength. This last group includes measures such as deposit rates (see e.g. Kraft and Galac, 2007) or indicators characterizing the economic environment in which the banks operate.[4]

B. Examples of Uses of the Early Warning Systems

There are two main potential uses for an early warning system such as the one we are trying to estimate in this paper. The first one relates to strengthening the role of rules in banking supervision, and decreasing the scope for discretion in decision making. The second 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 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 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 supervisory

[4] Rating agencies' assessments could also be considered in this category, even though those are typically based on a combination of financial ratios and market indicators, and are therefore largely a combination of the first two types of indicators.

authorities have been moving towards more formal, structured and risk-focused procedures for ongoing banking supervision, but there is still substantial scope for ad-hoc deviations.[5]

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, would be implemented at the EU level, it could give more confidence to supervisors in one EU member country that timely intervention will take place by supervisors in another EU member country. Mayes, Nieto, 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 IV 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 bank 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 re-estimated and reassessed to respond to new developments in the system—a point particularly relevant in today's European banking market.

An important limitation of the financial stability framework in the EU is that supervisors in individual EU member countries have different approaches to dealing with weak banks, a point made in previous work (Čihák and Decressin, 2007) and highlighted by the ongoing financial crisis. These cross-country differences may be less relevant for small banks with mostly local operations, but they are important for the large cross-border financial institutions (LCFIs) that came to dominate the EU financial landscape.[6] The legal, regulatory, and supervisory frameworks have not been able to keep up with this rapidly growing cross-border presence. The current crisis provides a window of opportunity for change while governments and parliaments are concerned.

The second argument, and 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 lead to lower 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 for introducing "Maastricht criteria" for financial institutions. As with the Maastricht criteria, which set debt and deficit limits for public

[5] This finding is consistent also with a recent survey 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.

[6] 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).

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 simple criteria that laymen can understand, and this information would be continuously disclosed. The difference to conventional rating agencies would be that these standards would be much more transparent and accessible to the public. 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.

It is unlikely to expect immediate miracles from such benchmarks for sound banking. As with the Maastricht criteria, the effect would come over time. Supervisors in one country would learn to trust supervisors in other countries as they implement interventions in the troubled banks, based on the common criteria. Customers would learn how to evaluate banks and have objective criteria at their disposal to choose the right financial institution for themselves. This should stimulate peer pressure and market discipline.

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}. 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:

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

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 model can also be represented in the form of the log odd's ratio:

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

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 the downward biased estimates of standard errors of the coefficients. To correct for the violation of the independence assumption, we employ a heteroskedasticity 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, i.e. 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 dataset 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 balance sheet and income statement data on 5,708 banks in EU-25 countries in 1996–2007.[7] We combine this with the second source, which is a unique set of data on bank distress. To put

[7] 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 their entry. One of the robustness checks we do consists of excluding pre-2004 observations in these countries.

together this database, we have 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. The database contains a wide range of local and global newspapers, newswires, trade journals, newsletters, magazines and transcripts.[8]

The NewPlus/Factiva searches were performed individually for each of the 5,708 banks, and for each year, using a combination of the bank name and the following six keywords: "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 have searched website of the relevant supervisory authorities for references to banks in distress. 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.[9]

Table 1 overviews the database. There are 5,708 banks from EU-25 countries in our sample with 29,862 bank-year observations in total. The NewsPlus/Factiva search provided us with hits for more than a 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.[10] Figure 1 provides a graphical overview of the number of distress episodes by country and by year, illustrating that the distress episodes are distributed far from evenly across the EU countries and years. Most of the distress episodes were located in Germany, which is also the EU country with the largest number of banks in the sample. Appendix III contains a detailed list of distressed banks and countries of their origin.[11] Most of the distressed banks are commercial, but there are also some specialized banks and credit institutions.

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[8] 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).

[9] For some EU banks in our list, we were not able to find any hits in NewPlus/Factiva. As a robustness check, we rerun our model after excluding observations on these "non-hitter" banks from our sample.

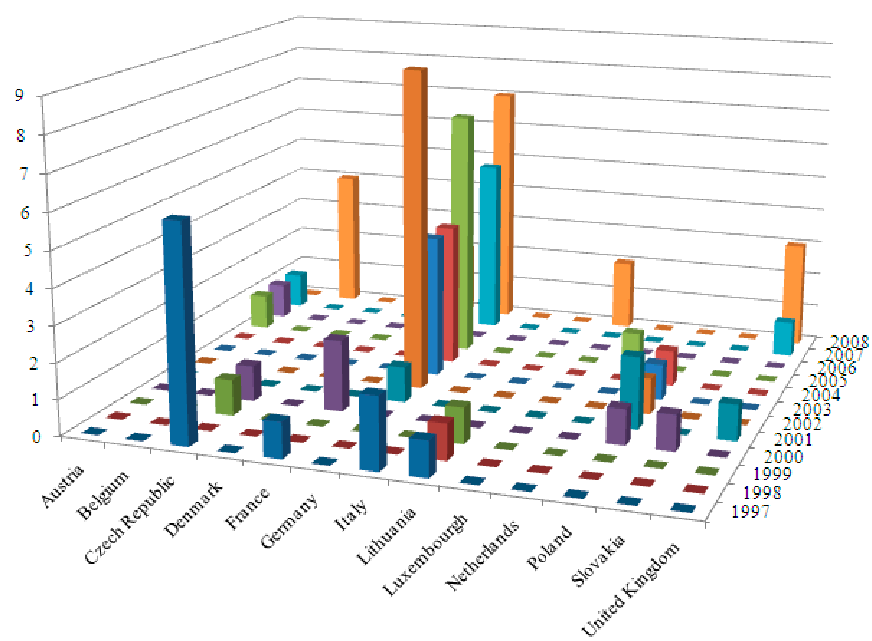
[10] The number of banks is lower than the number of distress events, since some banks experienced multiple distress over time.

[11] The appendix contains information on 75 distressed banks identified through the NewsPlus/Factiva search. The difference between total distressed banks and distressed banks used in our estimations is due to missing bank-specific information in BankScope.

Table 1. Database Overview

Country name	Bank-year observations			Banks		
	Distressed	Total	No hits	Distressed	Total	No hits
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

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



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 capitalization, asset quality, managerial skills, earnings and liquidity (CAMEL) of banks. We then proceed to introduce other potential determinants, namely those relating to depositor discipline (deposit rates), a variable capturing contagion effects among banks, a set of macroeconomic variables, a measure of market concentration, stock market indicators, and other variables.

The first CAMELS 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 have been arbitrary rather than based on an explicit model of risk (at least that has been the Basel I approach, which is what the banks were using in the period under review). 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-independent leverage ratio can be useful.[12] Indeed, recent policy discussions and steps in several countries (most prominently in Switzerland) led to a renewed emphasis on the basic leverage ratio as an important indicator of bank soundness.

As regards the second CAMELS 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 is approximated by the cost to income ratio, with lower values of this indicator suggesting better managerial quality. To measure bank earnings, 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 is measured by the ratio of liquid assets to deposits and short-term funding.

[12] Relatedly, Gropp and Heider (2008), examining a sample of banks and non-bank 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 non-bank corporations also apply to large, publicly traded banks.

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 (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 bank in the same country that has a similar size (total assets within the range of ±200 million Euro). The range is meant to capture the impact of the contagion effect spreading from the individual bank distress on its peers with comparable market size. Based on this range, we have identified 98 banks that are exposed to possible contagion effects. The size of the range is arbitrary, but our results are reasonably robust with respect to the choice of the range.

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 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.[13] It contains mean values for the determinants of financial distress for two groups of bank-year observations: distressed and non-distressed. It shows that, on average, the distressed banks have a lower level of capitalization and earnings and 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.

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

Table 2. Determinants of Bank Distress

	Non-distressed		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.

IV. Estimation Results

A. Baseline Estimate

We start by pooling observations for individual banks and estimating the baseline specification (2) using a logistic model that is robust to heteroskedasticity.[14] The baseline estimation result is shown in column (I) of Table 3.

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

Similarly, the PD is positively related to the declined asset quality. Assuming that the higher loan loss provision profile implies riskier loan portfolio, the positive sign in front of this variable indicates that the PD is influenced by the deterioration of 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 forthcoming year. This finding is in line with some of the previous research on other countries, for example with the results of Kraft and Galac (2007) for Croatia.

[14] 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.

The coefficient of the contagion dummy also came out positive highly significant. This suggests that financial distress in a bank influences not only 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 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 better (or worse) likelihood of preventing bank distress. Indeed, some of the distressed banks had very good cost-to-income ratios.

Liquidity also 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 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-sq, 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, we find that the results (reported all in Table 3) are rather robust with respect to the sample selection, additional explanatory variables, and various changes in the estimation methodology.

In specification (II), we conduct a robustness check with respect to bank relevance/size. As mentioned, our measure of bank distress is based on information collected from the search of databases of media reports. It is possible that a distress situation in a bank, especially in a small bank 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 very extensive and includes specialized business media (Section III.B). Nonetheless, as a robustness check aimed at testing this hypothesis, we delete from the sample all banks for which the NewsPlus/Factiva contains no information. These banks correspond to about one-third of banks, and generally these are indeed very small banks. In specification (II), we exclude these "non-hitters" from the sample and re-estimate the model. The estimation results 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-sq) did 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 at the level of the individual EU countries, which may have an impact on the individual PDs. Whether to expect these variables to have a significant impact is not clear. The early warning models for bank supervision usually focus on the relative risk in individual banks and do not adjust for macroeconomic variables (see Section III.B for a survey). But it is possible that macroeconomic variables do have an impact on bank risk. Indeed, some macroeconomic variables are significant in studies on early warning models for banking crises (see e.g. Čihák and Schaeck, 2007). For example, a higher inflation rate can make the macroeconomic environment less stable, implying 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 surge in bank credit (due to various reasons, e.g. financial liberalization) are found to be vulnerable to systemic banking crises (Beck, Demirguc-Kunt and Levine, 2006). On the other hand, the impact of these variables may well be relatively limited, given the degree of economic integration within the EU, and given that many of the banks have operations in more than one country.

In specification (III), we present estimation results for the baseline model augmented by several macroeconomic factors. We find that the variables capturing macroeconomic developments in individual countries do not have a significant impact on PDs in EU banks.[15] This suggests that given the degree of economic integration within the EU, and given that many of the banks have operations in more than one country, individual country macroeconomic variables have little or no power when trying to explain individual bank distress.

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

In specification (IV), we control for the effect of common shocks on the EU countries. An example of such a shock is the recent depreciation of the US dollar vis-à-vis the Euro and the other European currencies, which had an economic impact on all EU countries simultaneously, and could have an impact on bank PDs. To allow for this possibility, we include time dummy variables in our estimations. In model (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 in the past often struggle to improve their soundness and their reputation among customers. This results in repeated observations of distress in some banks.[16] Column (V) presents estimation results for a specification that includes only the first distress events and excludes the repeated observations of distress from the sample. The estimation 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. Theoretical literature provides ambiguous predictions about the relationship between market concentration and bank distress. One stream of studies, initiated by Allen and Gale (2000, 2004), focuses on bank liabilities, and predicts a negative relationship between market concentration and banks' risk of failure. Another stream of literature (e.g., Boyd and De Nicoló, 2005) shows that introducing competition in the loans market into the model (in addition to the competition in the deposits market) suggests a positive association between market concentration and banking risks. Boyd and others (2006) test these contrasting predictions empirically employing international panel of bank-level data, and using Herfindahl index as a proxy for competition among banks and the so-called Z-score as a proxy for bank risk. They find robust positive association between concentration and risk. In specification (VI), we augment the baseline specification by introducing the concentration variable for individual countries measured by the Herfindahl index (based on bank total assets). The results show a positive significant impact of market concentration on the PDs, suggesting that more concentrated banking markets are characterized by a relatively higher likelihood of bank distress.[17]

Related to the previous point, 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 return on asset ratio for the bank. The measure is designed to compare banks' buffers (capital and profits) with the risks

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[16] 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.

[17] The impact of market concentration, however, becomes insignificant when macroeconomic variables are also entered in the model specification.

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 (e.g., Boyd and others, 2006). Column (VII) shows estimation outcomes when the Z-score is added as an additional covariate into the baseline model. 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. Again, this is one of the topics 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; Curry, Elmer, and Fissel, 2001). However, the literature for other countries is generally less conclusive (e.g., Bongini, Laeven, and Majnoni, 2002), and even for the U.S. there 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 FTSE-100 market index.[18] The literature does not provide a strong prior, but a plausible hypothesis is 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. Therefore, one can expect a positive sign for this variable Specification (VIII) shows the estimation results with this stock price measure added to the baseline specification. The estimated coefficient is positive and significant, suggesting a positive association between deviations from stock market trends and bank PD in the next period.

We also explore the role of wholesale financing on the likelihood that the bank will experience financial difficulties in the future. Wholesale funding is usually rather granular (large in size) and it is not a part of the traditional deposit protection schemes. This makes wholesale lenders more jittery in the event of financial turbulence; this in turn makes the banks more vulnerable to sudden withdrawals. Recent evidence (e.g., in the case of Northern Rock) provides some examples of runs by retail depositors preceded by a run by wholesale lenders. We re-estimate the model by including the share of wholesale financing in bank total liabilities into our baseline specification. Estimation results reported in column (IX) suggest that banks that heavily rely on wholesale financing are more likely to experience financial distress relative to those banks that are mostly financed by retail depositors.

[18] Listed European banks were identified from Bankscope by their International Securities Identification Number (ISIN). Daily series of individual bank stock prices and FTSE-100 index are taken from Datastream. Market information variable takes value of 0 for the rest of (non-listed) banks. Because the logit estimate is based on annual data, we use yearly averages of the daily stock price data. We have also experimented with different approaches to mapping the daily data into yearly data, but it has little impact on the results.

We exploit the panel data structure of our sample by running two types of random effects models. Column (X) presents estimation results for the random effects model in which intercept varies at the individual bank level, while column (XI) presents estimation results for the random effects model in which intercept varies at the country level. Intuitively, the former model 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. Estimation results suggest that the estimate of the standard deviation is significant in specification (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}. It is also noticeable that both panel data specifications (X) and (XI) produce qualitatively similar results for the key financial indicators compared to 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 (and, potentially, also to the proposition of a common EU supervisory framework).

Finally, as an additional robustness test, we estimated the model only for those 19 failures that happened in 2008, i.e. only a cross section based on 2007 data, predicting the 2008 failures. The estimate, presented in column (XII), performs rather well in terms of the pseudo-Rsq, and in terms of its predictive power (it identifies 15 banks out of 19 if we set the cut-off point at PD=1 percent). Compared to the baseline estimate based on the full 1995–2007 sample, this estimate suggests that capitalization has a significant impact on the PD, and that managerial quality (insignificant in the baseline estimate) may play a role. At the same time, asset quality, significant for the full sample, does not show up significant for this reduced sample. The other variables, specifically the contagion dummy, the market discipline variable (i.e., the deposit rates), and the market information variable (i.e., the stock prices) have the same significance and similar values to the baseline estimate. This suggests that even though the distress of 2008 was clearly different from anything seen in the recent past, some mechanics of the model estimated on the longer panel data has remained in place even in the recent crisis.

The bottom line of all these robustness checks is that the baseline model performs reasonably well. The main advantage of the baseline model is that it is relatively parsimonious: it uses easy-to-calculate variables that could be used by laymen. We show that these variables are helpful in predicting actual distress events, and could potentially be used as a sort of "Maastricht criteria" for bank performance. The robustness checks suggest that the predictive power of these indicators does not change much when other potentially relevant control variables (such as those relating to the macroeconomic environment or market structure) are included or when different estimation methodologies are used.

Table 3. Logit Estimation Results

	(I) Baseline	(II) Excluding non-hitters	(III) With macro var-s	(IV) With time effects	(V) Only first distress	(VI) With concentration measure	(VII) With z-score	(VIII) With stock prices	(IX) With wholesale financing	(X) RE banks	(XI) RE countries	(XII) Only 2008 distress
Capitalization	-26.578**	-25.085**	-17.449	-22.166**	-21.218**	-28.551**	-14.820**	-27.466**	-30.268**	-37.059***	-29.239***	-44.490***
Asset quality	20.443**	18.737**	19.426**	16.725**	14.875**	18.950**	2.339	20.609**	18.187**	29.513***	19.368**	-67.735
Managerial quality	-0.109	-0.105	0.061	-0.102*	0	-0.107	-0.313*	-0.11	0.049	-0.119	-0.121*	-0.184**
Earnings	-1.911***	-1.790**	-1.653**	-2.324***	-1.101**	-2.377***	-6.099***	-1.957***	-1.868**	-2.360**	-2.125***	-4.357***
Liquidity	-0.405	-0.526	0.157	-0.316	-0.351	-0.246	-0.348	-0.413	-0.264	-0.886	-0.6	-0.614**
Market discipline	4.957***	5.082***	3.885***	4.446***	5.057***	4.649***	4.000***	4.974***	4.932***	7.724***	5.082***	5.182***
Contagion dummy	6.072***	5.829***	6.834***	7.041***	6.011***	5.956***	5.798***	6.086***	6.348***	8.756***	6.388***	3.377***
Inflation			0.000									
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								4.965***				5.341***
Wholesale liabilities (share)									0.163***			
Intercept	-5.494***	-5.173***	-6.068	-3.427***	-6.285***	-5.709***	-4.756***	-5.469***	-5.809***	-8.862***	-5.423***	-2.149***
Number of observations	29862	18164	29155	29862	29837	29862	29417	29862	27800	29862	29862	4358
Pseudo Rsq	0.480	0.469	0.613	0.551	0.462	0.490	0.497	0.485	0.506	0.4869	0.5196	0.3372
Log likelihood	-284.599	-270.216	-166.718	-245.84	-212.522	-279.307	-256.955	-282.266	-211.594	-247.822	-282.114	-112,167
Random error (log of st. dev.)	--	--	--	--	--	--	--	--	--	2.077***	-0.263	--

Notes: *, ** and *** indicate significance at 10, 5 and 1 percent levels, respectively. Rsq 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 of 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 setup a cut-off point in terms of the bank PD. All banks above that cut-off point are "black-listed" as weak banks, while all banks below that point are classified as healthy.

A higher cut-off point results in a lower number of banks on the "black list" of weak banks, which tends to increase the Type I errors. Setting a lower cut-off point can reduce the Type I errors, but at the expense of increasing the Type II error. There is no agreement in the literature on the optimal level of the cut-off point. That said, from a prudential perspective, relatively low cutoff points that limit the Type I errors, even if at the expense of relatively long "black lists" (and potentially high Type II errors) are often considered preferable. In what follows, we illustrate the sensitivity of Type I and Type II errors with respect to the choice of the cut-off point.

Table 4 displays the relative association between model predictions and actual distress events for our baseline specification using three different cut-off 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 non-distress events (99.7 percent) for the 10 percent cut-off 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 satisfactory in terms of correctly classifying distressed banks.

Table 4. Type I and Type II Errors

Cut-off 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

Cut-off 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

Cut-off 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

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

Figures 2 and 3 illustrate the distribution of banks in terms of the predicted PDs. Figure 3 shows the simple distribution of the PDs across banks without weighting them, while in Figure 2, the banks are weighted by their assets. The share of total bank assets at high level of risk (PD>1 percent) has been steadily growing 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 seeing rise at the end of the sample. 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

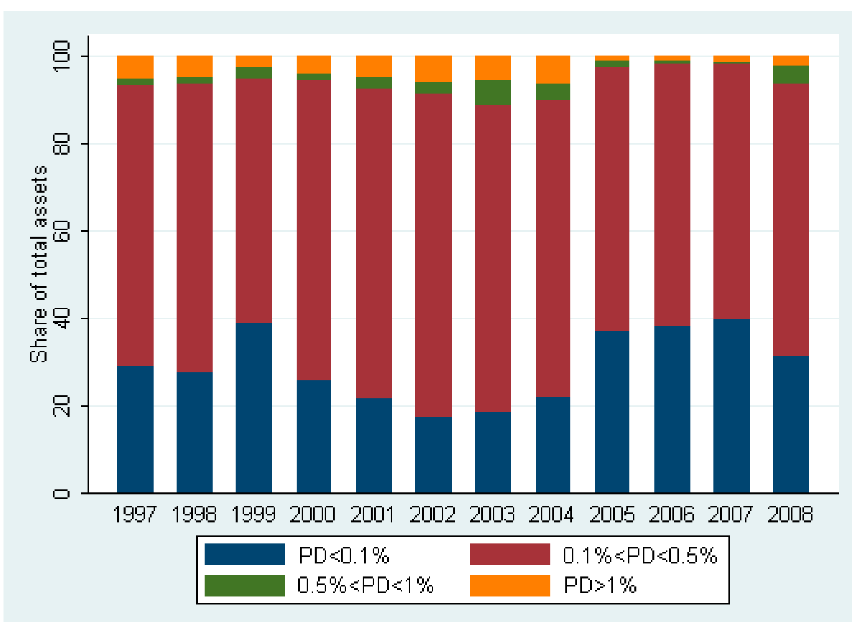
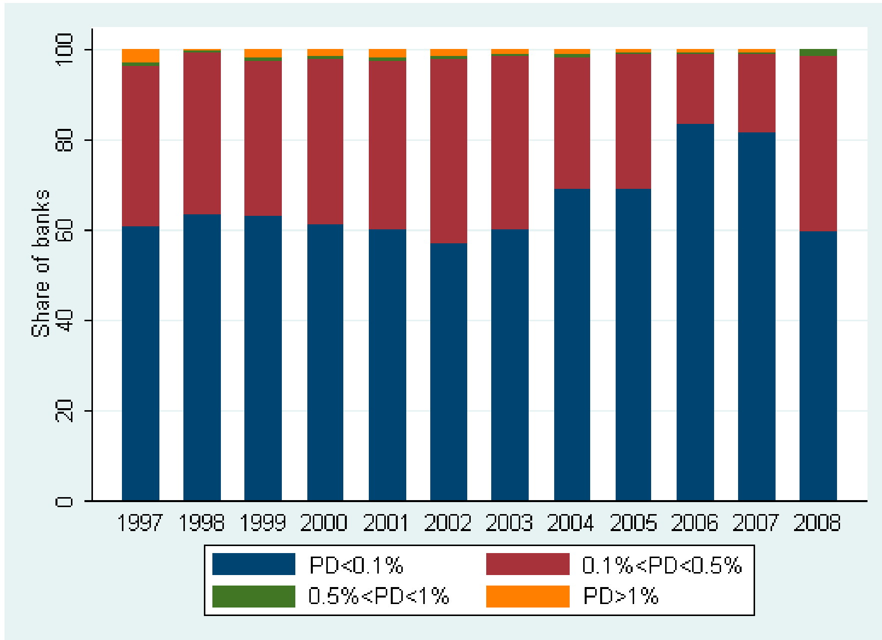


Figure 3. Assets at Risk



D. Marginal Effects

The coefficients of the logit model, as mentioned in the previous section, have a non-linear 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 of Figure 4 allows to identify the trigger points in the levels of these three covariates that result in an increase of bank PD above a given cut-off point. For example, if we choose the 10 percent cut-off point in terms of PDs (as 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 3-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, it can have its PD 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

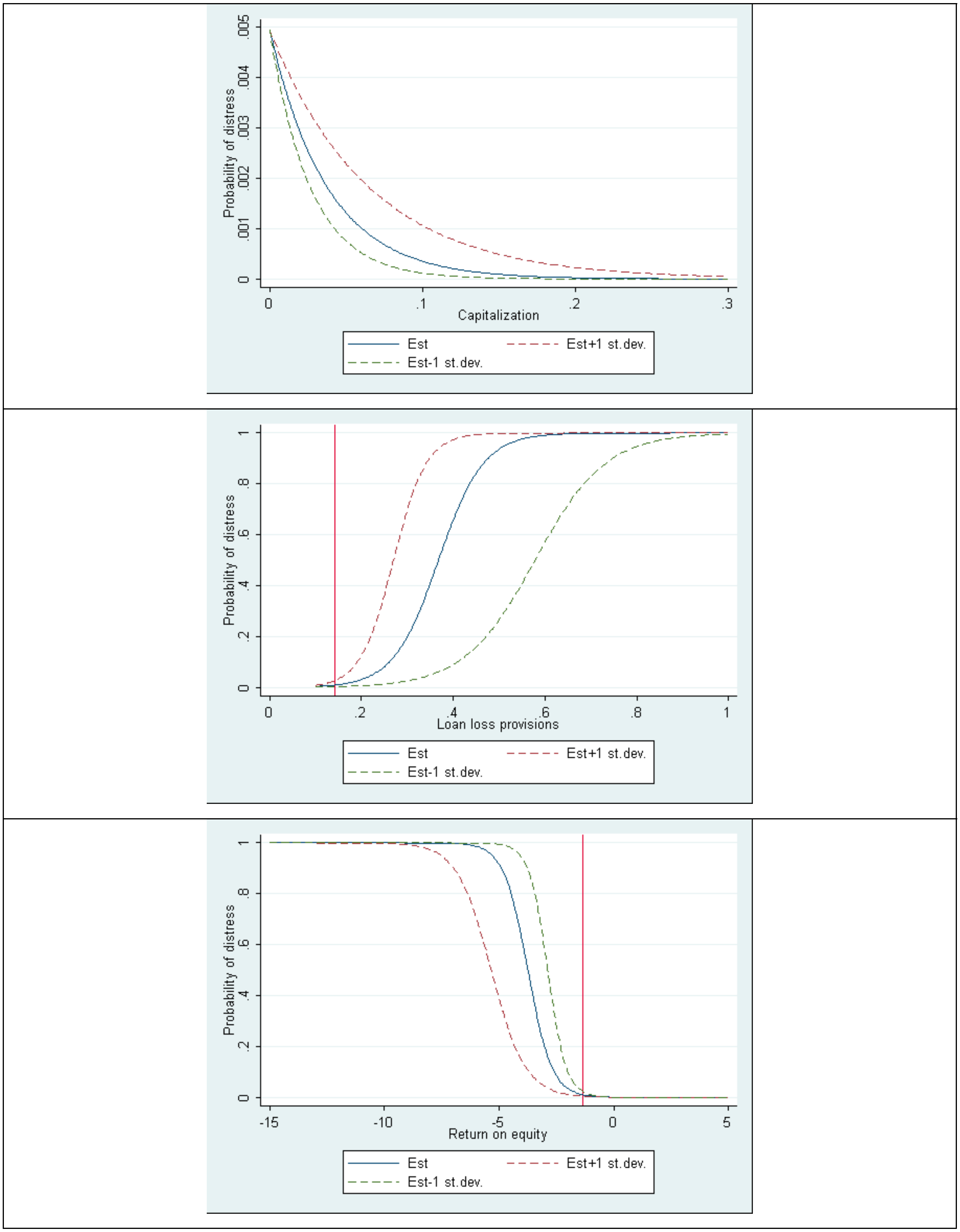
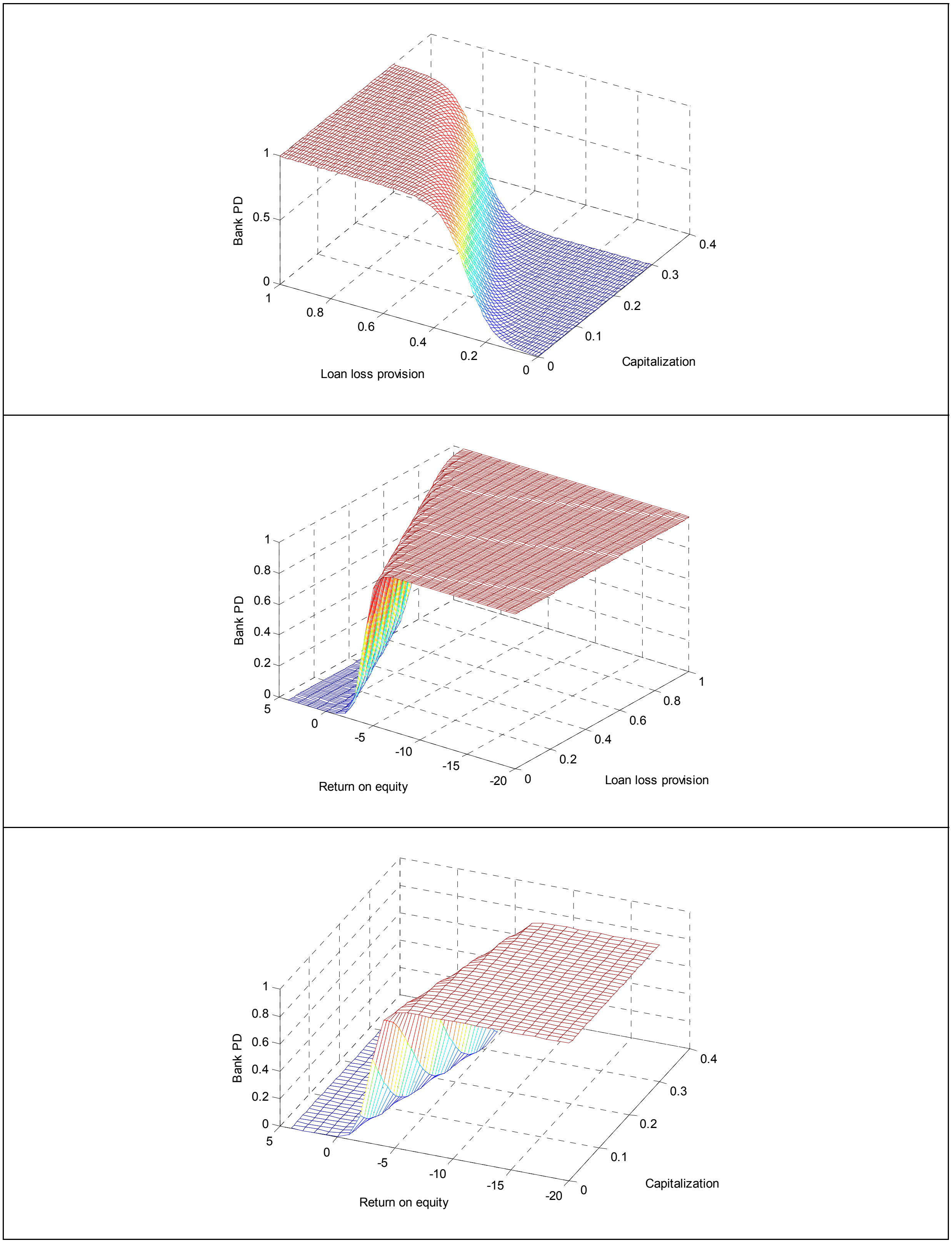


Figure 5. Trade-off in the Impact on PD between Pairs of Significant CAMEL Covariates


Bank PD
1
0.5
0
1
0.8
0.6
0.4
0.2
0
Loan loss provision
0
0.1
0.2
0.3
0.4
Capitalization
Bank PD
1
0.8
0.6
0.4
0.2
0
5
0
-5
-10
-15
-20
Return on equity
0
0.2
0.4
0.6
0.8
1
Loan loss provision
Bank PD
1
0.8
0.6
0.4
0.2
0
5
0
-5
-10
-15
-20
Return on equity
0
0.1
0.2
0.3
0.4
Capitalization

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 increased scrutiny. The thresholds would need to cover not only capitalization, but also other CAMELS variables, notably 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 plays an important signaling effect: when a bank pays more on deposits than its competitors, it significantly increases its probability of distress. Contagion effects play an important role as well: the probability of distress in a bank is significantly increased if there was a recent distress in a bank of a comparable size in the same country.

We also 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 CAMELS indicators.

We also find that more concentrated banking markets are characterized by a relatively higher likelihood of bank distress. In contrast, differences in the macroeconomic environment among the EU countries do not appear to play a significant role in predicting bank PDs. This may reflect the relatively high degree of economic and financial integration within the EU.

We find 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 to the proposition of a common EU supervisory framework.

The estimated early warning system provides a set of criteria for good banking performance. Such criteria could be useful for bank depositors and other creditors. Policymakers could use such criteria to limit the scope for supervisory forbearance and to 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 bank 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. It needs to, as suggested in a different context by King, Nuxoll, and Yeager (2006), be re-estimated and reassessed to respond to new developments the system—a point particularly relevant in today's European banking market.

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; King, Nuxoll, and Yeager, 2006). The financial ratio analysis generates a warning if a ratio exceeds a predetermined critical level, or 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. It 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 as compared to 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 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 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 CAMELS composite rating on the basis of the most recent call report data. Specifically, it estimates the probability that the bank's next composite CAMELS 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 CAMELS onsite rating and a list of about 45 financial and non-financial variables. Variables that are not statistically significant in predicting the composite CAMELS 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 prior composite CAMELS 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 CAMELS ratings for the respective institution. If the estimate is significantly different from the most recent onsite 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 US Federal Reserve also uses a version of the SEER model that estimates the probability that a bank will become "critically under-capitalized" 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 through 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" which includes a "peer analysis" and a "change analysis" for each individual 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, Deutsche Bundesbank uses a hazard rate model to model developments in 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 also 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 like credit culture, underwriting standards, 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 non-financial 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 backtesting 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 backtesting is carried out to ascertain whether the model correctly identifies banks that are likely to run into serious problems in the future. To test the efficacy of its GMS model, the FDIC compares GMS composite scores with future bank failure rates. The analysis shows that banks in the lowest GMS score decile usually fail at the highest rate during the two years immediately after the scores were measured and those in the highest GMS 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 in the future 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 are now 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, it has been in limited contexts. The challenge of 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 has proven to be difficult.

Since early warning models are a relatively new development, it is not surprising that further work is being carried out to improve their performance. Possible future lines of action include:

- Developing models using market-based indicators such as spreads on subordinated debt.
- Use of economic data in early warning models. Given the growing trend of consolidation and geographical diversification of the banking industry, national and international economic conditions assume greater relevance in their impact on bank performance.
- Increasing the use of models for stress testing and scenario analysis.

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 emerging , 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, 2005). There is a rapidly growing number of LCFI that 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 (Trichet, 2007).[19] 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.

Financial Stability Framework for Europe

The IMF has been arguing that the EU needs a more integrated approach to financial stability (IMF, 2007 and 2008). This fact has been highlighted by the financial turmoil. 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 requires an integrated approach to financial stability.[20] Political preference as well as legal and institutional considerations have thus far limited the progress on cross-border financial stability arrangements; however, the increased sense of urgency created by the ongoing financial turmoil has bolstered support for reforms in this area.

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 (including 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. These principles, adopted by the October 2007 ECOFIN,

[19] Further information on the mapping exercise can be found for example at ECB (2005, 2006).

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

commit member states to act in crises to minimize the "potential harmful economic 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 rulemaking 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 non-binding nature of the guidelines.

Strong political leadership will be needed to move decisively toward greater joint responsibility and accountability. The crisis-management principles, with their recognition of a collective responsibility and a need to share costs, are mould-braking. However, in a severe crisis, national interests may still prevail over the good intentions embedded in these principles and the non-binding MoU. The MoU also risks further adding complexity to the cross-border financial stability set-up. 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. It this context, an important step was taken at the May 2008 ECOFIN meeting, which called on member states to endow their supervisors' statutes with a European mandate so that they "are able to take into account the EU dimension in the performance of their duties, including having regard to the financial stability concerns in other Member States in exercising their duties." However, as emphasized by the IMF (2008), "bolder steps will be needed … that will require strong political leadership—of the kind that led to the introduction of the euro 10 years ago."

APPENDIX III. LIST OF DISTRESSED BANKS

Bank	Country	Bank	Country
BAWAG PSK Group	Austria	Roskilde Bank	Denmark
BAWAG Wohnbaubank	Austria	Banque Worms	France
Dexia	Belgium	CIC Paris	France
Dexia Bank-Dexia Bank Belgium	Belgium	Crédit Foncier de France	France
Fortis	Belgium	Crédit Lyonnais	France
COOP Banka	Czech Republic	Dexia Crédit Local SA	France
Ceska Sporitelna	Czech Republic	Locindus	France
Foresbank	Czech Republic	Natixis	France
Investicni a postovni banka	Czech Republic	Société Marseillaise de Crédit	France
Komercni Banka	Czech Republic	Allgemeine Hypothekenbank	Germany
Moravia Banka	Czech Republic	B. Metzler seel Sohn & Co Holding	Germany
Pragobanka	Czech Republic	BHF-Bank	Germany
Union Banka	Czech Republic	BHW Holding	Germany
Univeresal Banka	Czech Republic	Bayerische Hypo-und Vereinsbank	Germany
eBanka as	Czech Republic	Bayerische Landesbank	Germany
Hungarian Development Bank	Hungary	Berlin-Hannoverschen Hypothekenbank	Germany
Sachsen LB Europe	Ireland	Consors Discount-Broker	Germany
Banca Agricola	Italy	DAB Bank	Germany
Banca Monte Parma	Italy	Deutsche Hypothekenbank	Germany
Banca Nazionale del Lavoro	Italy	Dresdner Bank	Germany
Banca di Roma	Italy	Duesseldorfer Hypothekenbank	Germany
Banco di Napoli	Italy	Frankfurter Sparkasse	Germany
Banco di Sicilia	Italy	Gontard & Metallbank	Germany
Bipop	Italy	HSH Nordbank	Germany
Caripuglia	Italy	Hypo Real Estate Bank	Germany
Lithuanian State Commercial Bank	Lithuania	IKB Deutsche Industriebank	Germany
Litimpeks Bank	Lithuania	KfW Group	Germany
Dexia Banque Internationale à Luxembourg	Luxembourg	Landesbank Berlin Holding	Germany
Fortis Banque Luxembourg	Luxembourg	Landesbank Berlin	Germany
Fortis	Netherlands	Landesbank Hessen-Thueringen	Germany
Van der Hoop Bankiers	Netherlands	Metzler Bank	Germany
BRE Bank	Poland	Sachsen LB-Landesbank Sachsen	Germany
Bank Gospodarki Zywnosciowej	Poland	WestLB	Germany
Bank Przemyslowy	Poland	Alliance & Leicester	United Kingdom
Kredyt Bank	Poland	Gainsborough Building Society	United Kingdom
AG Banka	Slovakia	HBOS	United Kingdom
Devin Banka	Slovakia	Northern Rock Building Society	United Kingdom
		Northern Rock	United Kingdom

APPENDIX IV. 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 and Wall, 2006).

A SEIR framework for cross-border systemic banks in the EU would need to aim at preventing failures and restoring failed banks to health. Mayes, Halme and Liuksila (2001) and Eisenbeis and Kaufman (2005) propose specific efficient resolution procedures. Summarizing their contributions, one could propose a general resolution procedure along the following lines:

- 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 (e.g., no dividend payments; limits on growth, new lending, and position-taking in financial markets);
- 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, the 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 of these operations 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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