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Determinants of Bank Distress in Europe: Evidence from a New Data Set

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Abstract Using a unique data set on bank distress, this paper provides novel empirical evidence on the determinants of bank soundness in the European Union (EU) as a whole. The estimation results are consistent with the hypothesis that bank risks have converged across EU members, providing empirical support for introduction of a more centralized system of financial regulation in the EU. We show that asset quality and earning profile of banks are important determinants of bank distress next to leverage, suggesting that these should be central in EU-wide financial regulation and supervision. We find that market discipline, both by depositors and by stock market participants, plays a role in the EU, supporting the notion that transparency and dissemination of financial information would contribute to the financial soundness of banks. Our data also point to the presence of contagion effects, relatively higher fragility of concentrated banking sectors, and hazards associated with high ratios of wholesale funding.

Keywords Bank distress · Banking regulation · Basel II Accord · Market discipline

JEL G21 · G28

1 Introduction

The global financial crisis has highlighted the importance of early identification of weak banks: when problems are identified late, solving them is much more costly. Early identification of weak banks ranks high on the agenda of European policymakers, given the apparent contradiction between increased cross-border financial integration in the EU and still mostly country-based prudential frameworks. Inspired by the global financial crisis, EU authorities have recently agreed to move towards a more centralized EU-wide prudential system (as proposed by De Larosiere 2009). An important argument in favor of a more

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centralized prudential framework in the EU is the notion that risks in the banking sectors of EU members have become increasingly homogenous due to increased financial integration. However, the literature lacks a rigorous cross-country analysis of determinants of bank distress in the EU.

The aim of this paper is to fill this gap. Unlike previous studies that focused on individual countries or on groups of countries outside of the EU,[1] we create and analyze a comprehensive database of bank distress covering the whole EU. The database covers periods before and during the global financial crisis, providing first evidence on the impact of the crisis on sources of distress in individual banks. Another innovation in the paper is that, departing from the previous studies, our definition of distress is not derived from financial ratios. This helps to overcome endogeneity problems when modeling determinants of bank distress and allows testing whether sources of bank risks have converged across EU members.

The paper also contributes by providing evidence on the importance of two pillars of the Basel II Accord (namely, bank capitalization and market discipline) as determinants of bank distress. The Basel II Accord emphasizes the importance of bank capitalization (inverse of the leverage) as the main driving factor for financial soundness of individual banks. The importance of bank capitalization for bank soundness is also highlighted in the proposal to establish a pan-European system of banking supervision (De Larosiere 2009). However, bank soundness can be also affected by other sources of risk, such as credit risk, liquidity credit, and earnings profile (the CAMEL profile of banks), among others. We provide evidence on the relative strength of different sources of bank risks other than capitalization in the EU.

Another pillar of the Basel II Accord is the market discipline, according to which disclosure of financial information is essential for market participants, such as depositors and investors, to identify weak banks and engage into preemptive measures. Studies based on the 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 et al. 2003). The literature for non-U.S. banks is less conclusive (e.g., Bongini et al. 2002; Čihák 2007). We provide evidence on the importance of the market discipline for the EU as a whole. We also test relative importance of other potential sources of bank distress, such as contagion effects, macroeconomic environment, market structure, and wholesale funding.

As a brief preview of main findings, this paper shows that sources of bank risk have converged across EU, and lends empirical support to establishing EU-wide benchmark criteria for banking sector soundness. However, our analysis highlights the importance of other sources of bank risk in addition to leverage, such as asset quality and earning profile, which should be taken into account when designing EU-wide benchmark criteria for bank soundness. The analysis also brings evidence on the importance of market discipline on the

[1] Most of the 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 (see, e.g., Lane et al. 1986, Cole and Gunther 1995, Calomiris and Mason 2000, Estrella et al. 2000, and Wheelock and Wilson 2000). Among individual country studies outside the United States, see Gonzalez-Hermosillo et al. (1997) for Mexico, Persons (1999) for Thailand, and Kraft and Galac (2007) for Croatia, and Kick and Koetter (2007) for Germany. Cross-country studies are Bongini et al. (2002) for five East Asian countries, Arena (2008) for five East Asian and three Latin Americal countries, and Mannassoo and Mayes (2009) for 19 Eastern European transition countries (country coverage in the latter study partially overlaps with ours, but does not cover the post-2004 period).

side of both depositors and stock market participants, which highlights the need for information disclosure and dissemination of bank soundness benchmarks as a part of the design of the more centralized system of financial regulation in the EU. Rigorous analysis of past incidences of bank distress also emphasizes the significance of contagion effects across EU banks. Furthermore, in line with the "concentration-fragility" view (Boyd and De Nicolo 2005), banks located in more concentrated banking sectors are found to be more vulnerable to distress relative to banks located in less concentrated industries. Lastly, we provide evidence supporting the notion of the "dark side" of bank wholesale funding (Huang and Ratnovski 2010).

The rest of the paper is structured as follows. Section 2 provides the estimation methodology and discusses the data being used. Section 3 reviews determinants of bank distress used in the analysis. Section 4 presents the estimation results. The last section concludes.

2 Data and methodology

2.1 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.[2] 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.[3]

The NewsPlus/Factiva searches were performed for each of the 5,708 banks, and for each year, using a combination of the bank name and keywords designed to capture references to failing banks: "rescue," "bailout," "financial support," "liquidity support," "government guarantee," and "distressed merger." When a search for a bank led to a hit (or a number of hits), we examined the highlighted media reports in more detail, to confirm that the 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.[4]

[2] 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. This is confirmed by one of the robustness checks, in which we exclude pre-2004 observations in these countries.

[3] 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).

[4] 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 it becomes subject to negative reports in the media. This is of course not the only possible definition of distress. It is a relatively broad definition that includes not only cases of outright failures and bank closures (those are included in the sample, but they have been relatively few in EU to allow for a meaningful analysis on a stand-alone basis), but also cases when a bank gets into serious enough trouble that its problems (and any associated responses, such as a government rescue or a forced merger with a healthier bank) are noticed in the media. Of course, some banks may go through stressful periods without the media's noticing—capturing this would require an even broader definition of distress than we are using (and a source of data that is currently unavailable on an EU-wide basis).[5] Nonetheless, defining bank distress through the lens of media is relevant 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.[6]

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 in 54 banks, meaning an average distress frequency of about 0.3% per year.[7]

The distress observations are not distributed evenly across the EU countries and across years, although they do mirror the general distribution of the number of banks in the sample (Fig. 1). Most of the distress episodes occurred in Germany, the EU country with the largest number of banks in the sample. Most of the distressed banks are commercial, although there are some specialized banks in distress.

2.2 Estimation methodology

To evaluate the impact of financial indicators on the probability of bank distress (PD), we follow the recommendation by Shumway (2001) and 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}.[8] 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:

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

[5] 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 (without any accompanying keywords), and, as a robustness check, we rerun our models excluding observations on banks for which these searches returned no hits.

[6] 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.

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

[8] In the baseline estimate, we lagged the explanatory variables by one period, i.e., 1 year. As a robustness check, we also experimented with 2-year and 3-year lags. These checks yielded results that were very similar, but weaker in terms of statistical significance (especially for the 3-year lags), suggesting that the predictive power of the explanatory variables declines as we attempt to predict failures further into the future.

Table 1 Database overview

Country name	Bank-year observations			Banks		
	Distressed	Total	No-hitters	Distressed	Total	No-hitters
A. Commercial Banks						
Austria	3	418	41	1	74	8
Belgium	2	212	16	2	41	5
Cyprus	0	75	4	0	12	1
Czech Republic	6	118	13	6	22	2
Denmark	1	460	274	1	63	37
Estonia	0	39	0	0	5	0
Finland	0	38	5	0	9	1
France	5	1,346	919	4	248	177
Germany	9	1,426	128	5	241	23
Greece	0	94	33	0	25	9
Hungary	0	106	61	0	17	11
Ireland	0	99	50	0	25	11
Italy	1	557	386	1	180	126
Latvia	0	164	17	0	22	3
Lithuania	3	87	9	2	12	1
Luxembourg	2	679	574	2	127	111
Malta	0	49	31	0	7	5
Netherlands	0	170	107	0	43	27
Poland	4	212	8	2	40	2
Portugal	0	38	23	0	12	7
Slovakia	1	105	0	1	16	0
Slovenia	0	101	30	0	16	6
Spain	0	317	184	0	92	55
Sweden	0	112	70	0	21	15
United Kingdom	2	534	393	1	127	88
Total	39	7,556	3,376	28	1,497	731
B. Other Banks (excluding commercial)						
Austria	0	1,315	284	0	212	50
Belgium	2	293	78	2	59	18
Cyprus	0	24	4	0	6	1
Czech Republic	1	20	2	1	7	1
Denmark	0	335	295	0	52	44
;Estonia	–	–	–	–	–	–
Finland	0	36	2	0	9	1
France	2	1,572	1,228	2	286	227
Germany	28	14,512	3,260	15	2382	608
Greece	0	23	1	0	6	1
Hungary	0	26	10	0	8	5
Ireland	0	74	46	0	20	10
Italy	1	2,163	1,972	1	696	639
Latvia	–	–	–	–	–	–

Table 1 (continued)

Country name	Bank-year observations			Banks		
	Distressed	Total	No-hitters	Distressed	Total	No-hitters
Lithuania	–	–	–	–	–	–
Luxembourg	0	85	52	0	21	13
Malta	–	–	–	–	–	–
Netherlands	1	116	69	1	29	17
Poland	2	29	3	1	5	1
Portugal	0	61	32	0	18	11
Slovakia	0	19	0	0	5	0
Slovenia	0	6	4	0	3	2
Spain	0	427	319	0	145	120
Sweden	0	485	436	0	97	86
United Kingdom	3	685	225	3	145	53
Total	40	22,306	8,322	26	4,211	1,908

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.

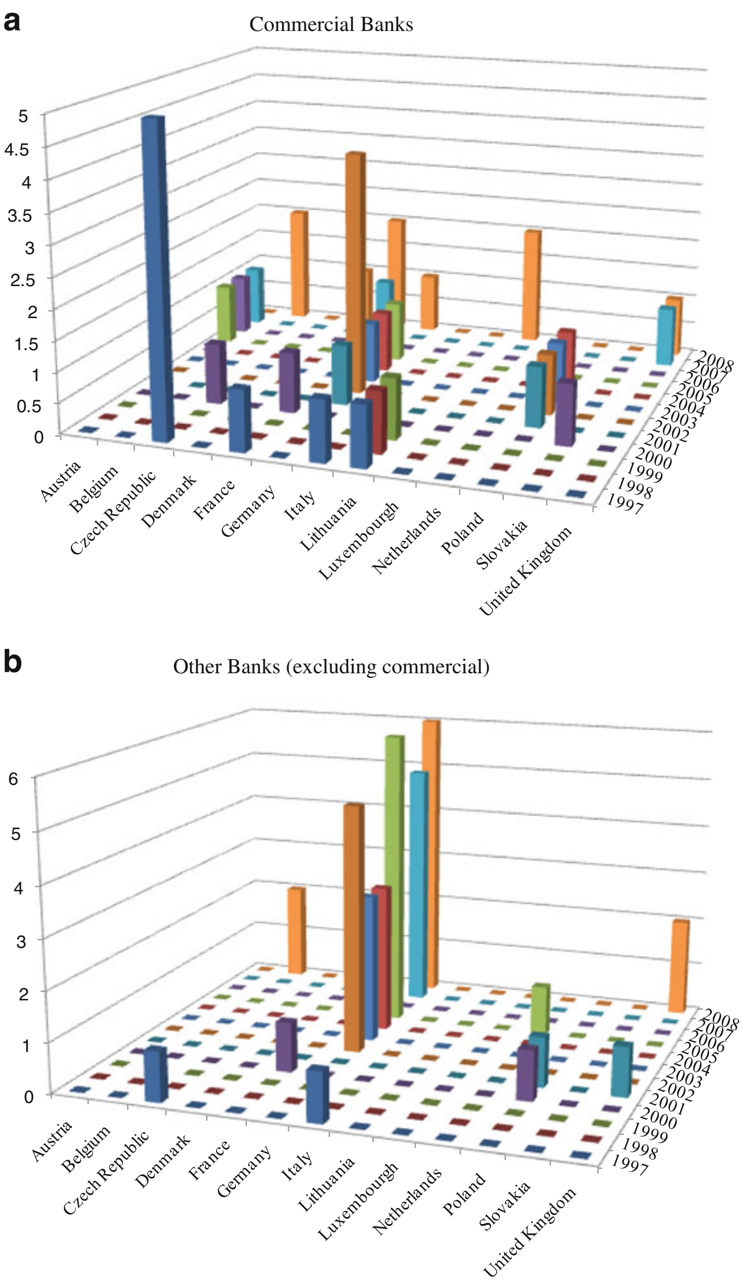
The logistic (logit) model can also be represented in the form of the log odd's ratio:

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

where $P_{ijt} = Prob(Y_{ijt} = 1 \mid X_{ijt-1})$ 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 (a common approach in the literature).

The logit model can be estimated in several ways. The simplest approach assumes independence of errors across individual banks, countries, and time. However, this assumption is likely to be violated in reality, and neglecting the violation of the independence of errors assumption would lead 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



Source: authors, based on searches in NewsPlus/Factiva.

Fig. 1 Overview of distress events by year and by country, 1997–2008. For EU countries that are not reported, no bank distress was identified in the sample period. **a** Commercial banks. **b** Other banks (excluding commercial). Source: authors, based on searches in NewsPlus/Factiva 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.[9]

3 Determinants of bank distress

3.1 CAMEL covariates

We use financial indicators of banks to generate determinants of bank distress (X_{ijt-1}). Following the 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 (inverse of the leverage), 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 main 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, 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.[10] 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 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%) 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-

[9] In addition to the logit model, we have also considered using a survival time model. However, given that our panel data set has a rather large number of banks (5,708) combined with a relatively short time span (11 years) and observations of distress (79). most of the dependent variable in the survival analysis (time until failure) is censored. In such setting, the survival time model has a relatively low value added, essentially only confirming that factors that tend to decrease the probability of distress in a bank also increase that bank's survival time.

[10] 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.

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.

3.2 Other determinants of bank distress

In addition to the CAMEL covariates, we also include a number of other potential explanatory variables. Specifically, to measure 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 theoretical (Hellmann et al. 2000) and empirical (Rojas-Suarez 2001; Kraft and Galac 2007) literature, 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 one 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 to 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.[11]

For robustness checks, we add a number of additional explanatory variables, which include macroeconomic variables (at the country level, gathered from the IMF’s International Financial Statistics), a measure of market concentration (calculated from the BankScope data), and stock market indicators (from DataStream).

3.3 Descriptive statistics

A basic analysis of the main determinants of bank distress for commercial and other (specialized) banks (Table 2)[12] suggests that, on average, the distressed banks have a lower level of capitalization (i.e., are highly leveraged) 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 cost-to-income ratios for other (specialized) banks, are significant at the 10% confidence level. The comparison of means suggests significant differences for fewer determinants of distress. 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.

[11] 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 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).

[12] 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 Descriptive statistics

	Nondistressed		Distressed		Mean Equality Test (*t*-test, unequal variances)		Median Equality Test (Wilcoxon test)	
	mean	median	mean	median	difference	*p*-value	difference	*p*-value
A. Commercial Banks								
(Total equity)/(Total assets)	0.0992	0.0738	0.0523	0.0393	−0.0470	0.0000	−0.0344	0.0000
(Loan loss provisions)/(Total loans)	0.0076	0.0042	0.0353	0.0087	0.0278	0.0176	0.0046	0.0004
(Total costs)/(Total income)	0.7431	0.7386	1.0554	1.0247	0.3123	0.2941	0.2861	0.0000
(Profit before taxes)/(Total equity)	0.1273	0.1175	−0.6063	0.0045	−0.7336	0.1982	−0.1130	0.0000
(Liquid assets)/(Total assets)	0.2974	0.1928	0.1571	0.1210	−0.1403	0.0003	−0.0718	0.0915
(Interest expences)/Deposits	0.0498	0.0358	0.0902	0.0576	0.0404	0.0031	0.0218	0.0000
B. Other Banks (excluding commercial)								
(Total equity)/(Total assets)	0.0705	0.0558	0.0369	0.0313	−0.0336	0.8976	−0.0245	0.0000
(Loan loss provisions)/(Total loans)	0.0076	0.0062	0.0235	0.0040	0.0159	0.1155	−0.0022	0.1920
(Total costs)/(Total income)	0.8129	0.8216	1.2095	0.8411	0.3966	0.5229	0.0195	0.4863
(Profit before taxes)/(Total equity)	0.1068	0.1005	0.0844	0.0257	−0.0224	0.5111	−0.0748	0.0000
(Liquid assets)/(Total assets)	0.2607	0.2345	0.4798	0.3057	0.2191	0.0312	0.0712	0.0345
(Interest expences)/Deposits	0.0421	0.0325	0.1569	0.0952	0.1148	0.0004	0.0627	0.0000

4 Estimation results

4.1 The baseline model

We start by pooling observations for individual banks and estimating (2) using a logistic model that is robust to heteroscedasticity.[13] The baseline estimation results (Table 3, column I) 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.

The impact of two CAMEL covariates, managerial quality and liquidity, was not found to be significant. As regards managerial quality, it is possible that the cost-to-income ratio used in our analysis is not a perfect measure of relative bank performance, since it does not

[13] 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.

Table 3 The baseline specification

Models	(I) Baseline model	(II) Excluding non-hitters	(III) With time effects	(IV) Only first distress	(V) Excluding Germany	(VI) Only Commercial banks	(VII) Excluding commercial banks
Capitalization	−26.578**	−25.085**	−22.166**	−21.218**	−26.259***	−13.008	−57.560**
Asset quality	20.443**	18.737**	16.725**	14.875**	10.054	16.567**	25.382***
Managerial quality	0.109	0.105	0.102*	0.000	0.192	0.350	0.250
Earnings	−1.911***	−1.790**	2.324***	−1.101**	0.698**	−1.204**	−2.092**
Liquidity	0.405	0.526	0.316	0.351	−1.990	−1.627*	0.900
Market discipline	4.957***	5.082***	4.446***	5.057***	4.476***	4.115***	4.985***
Contagion dummy	6.072***	5.829***	7.041***	6.011***	5.750***	4.809***	7.728***
Intercept	−5.494***	−5.173***	−3.427***	−6.285***	−7.447***	−5.269***	−4.352***
Number of obs.	29,862	18,164	29,862	29,837	13,924	7,556	22,306
Pseudo $R-$sq.	0.480	0.469	0.551	0.462	0.516	0.443	0.554
Log likelihood	−284.6	−270.2	−245.8	−212.5	−138.3	−136	−130.5

*, **, and *** indicate significance at 10, 5, and 1% levels, respectively.

take into account input prices and output of banks.[14] The fact that it does not come out significant may suggest that low costs do not necessarily indicate a lesser likelihood of experiencing distress in the future (indeed, some of the distressed banks had very good cost-to-income ratios). As for insignificant impact of liquidity, the result is not very surprising given that we are trying to identify distress over a 1-year window, while our measure of liquidity only reflects the amount of liquid assets banks hold in their portfolio at the last day of financial reporting (i.e. does not account for substantial variation of liquidity over time). When a bank's problems turn into a liquidity problem, it is often only very shortly (i.e., days) before the failure (or intervention) and our liquidity measure might not capture these developments.[15]

Among non-CAMEL determinants of bank distress, we found significant evidence in favor of the market discipline hypothesis and contagion effects. Our results suggest that 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.[16] In addition, we find that financial distress in a bank not only influences the bank itself, but it also significantly increases PDs of its peers in the market, as indicated by highly significant positive coefficient of the contagion dummy.[17]

Overall, despite its parsimoniousness, the baseline model fits the data rather well. This is illustrated for example by the pseudo R-squared, which is 0.48 for this baseline estimate. This value compares favorably with similar models in the early warning system literature (see, e.g., Bongini et al. 2002).

4.2 Robustness check

To assess the reliability of the baseline results, we employ a battery of robustness checks (Table 3, columns II–VI). Overall, the results are rather robust with respect to the sample selection, time effects, and repetitive distress incidences.

As discussed earlier, NewsPlus/Factiva searches did not return results for almost a third of banks in our sample. These banks are mostly small in size and one could argue that outright bank distress in some of these banks could go completely undetected, in which case our results might be affected by the selection bias. To check for this possibility, we re-estimate the baseline model after excluding these "non-hitters". The results (reported in column II) are very similar to the baseline model, suggesting that there is little evidence of selection bias.[18]

[14] The results might have been 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 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 (see, e.g. Mannasoo and Mayes 2009).

[15] 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.

[16] This is consistent with the theoretical prediction of the model by Hellmann et al. (2000).

[17] This result is robust to alternative measures of contagion dummy. Instead of defining similarity among banks as asset size within EUR ±200 million we re-estimated the model by (i) defining "similar size" as EUR ±100 million and (ii) employing 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).

[18] Since the model fit (pseudo R-squared) does not improve after this sample reduction, we proceed with using the total sample in our subsequent estimations.

Next, we account for the possibility that bank distress might be affected by common shocks (such as shocks to the euro-dollar exchange rate) affecting EU countries simultaneously. To control for common shock effects, we include time dummy variables in our estimations (specification III). 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 (with the exception of managerial quality) remain unchanged, supporting the robustness of our results.

Further, we account for the possibility that banks that have already experienced financial difficulties might struggle to improve their reputation and might be prone to repeated incidences of distress.[19] To control for the impact of this "stigma effect", we re-estimate the model after excluding the repeated observations of distress. The estimation results (reported in column IV) corroborate our findings for the baseline specification, suggesting that our main results are not driven by the "stigma effect".

Lastly, we check the extent to which our results might be driven by the dominance of certain countries and certain organizational structures of banks experiencing distress. To check for the country dominance, we run separate estimation of the baseline model by excluding Germany (which accounts for 37 out of 79 distress events) from the sample. Estimation results (column V) 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, rejecting the country dominance notion. To check for the organizational structure dominance, we re-estimate the baseline specification for only commercial banks (column VI), which account for about half of the observations of bank distress (39 out of 79), and for the rest (column VII) pertaining to savings banks, cooperative banks, specialized governmental institutions, bank holding companies, investment banks, and real estate banks (separate estimations for these organizational forms of banks were not possible due to insufficient number of observations). The estimation results suggest that our findings are applicable also to commercial and other (specialized) banks separately, as all qualitative findings (except from the impact of capitalization and liquidity for commercial banks) remain unchanged.

4.3 Introducing additional control variables

As a next step, we augment the baseline model by introducing additional control variables (Table 4). The purpose of this analysis is twofold. First, we want to confirm that our main conclusion that capitalization, asset quality, earnings, market discipline on the side of depositors, and contagion hold when additional control variables are accounted for. Second, we would like to test whether macroeconomic environment, market structure, market discipline on the side of stock markets, and wholesale financing significantly affect the likelihood of bank distress.

Previous literature suggests that some macroeconomic variables can be important predictors of systemic banking crises (see, e.g., Berg et al. 2004; Demirguc-Kunt and Detragiache 1999; Beck et al. 2006; Čihák and Schaeck 2007). For example, a higher rate of growth and lower inflation rate can be associated with a more stable macroeconomic environment and a relatively low likelihood of bank distress. Similarly, the financial deepening of the local economy can have implications in terms of financial stability (e.g., Beck, et al. 2006 show that countries experiencing surges in bank credit are found to be

[19] 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.

prone to systemic banking crises). On a superficial look, our estimates (Table 4, specification I) seem to suggest that the variables capturing macroeconomic developments in individual countries do not have a significant impact on PDs in EU banks.[20] This appears to contradict the literature on systemic banking crises discussed earlier, where macroeconomic factors often play a significant role. However, upon closer examination, the apparent contradiction can be explained. In particular, there are two important differences between the above 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, in line with much of the systemic banking crisis literature, while the rest of the estimates is basically unchanged.[21] This suggests that the macroeconomic factors do have some, even though a quantitatively small, impact on bank distress in individual countries.[22] 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 (illustrated by, e.g., relatively low cross-country differences in inflation rates, and relatively high—although not perfect—synchronization of business cycles) 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.

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 (column II). 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.

Further, we evaluate the extent to which stock market information may be helpful in predicting bank distress (market discipline hypothesis on the side of stock market participants). 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 et al. 2003). The literature for other countries is generally less conclusive (e.g., Bongini et al. 2002), and even for the United States, there is some evidence on the weakness of market prices in predicting bank failures (Gilbert 2002). To evaluate whether stock markets impose discipline on banks as suggested by one of the Basel II Accord pillars, we augment the

[20] To keep Table 4 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.

[21] Results for this iteration of the robustness check are not shown in Table 4, but are available upon request.

[22] 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.

Table 4 The baseline model augmented by additional control variables

Models	(I) Macro	(II) Market	(III) Stock prices	(IV) Wholesale
Capitalization	−17.449	−28.551**	−27.466**	−30.268**
Asset quality	19.426**	18.950**	20.609**	18.187**
Managerial quality	0.061	0.107	0.110	0.049
Earnings	−1.653**	−2.377***	−1.957***	−1.868**
Liquidity	0.157	0.246	0.413	0.264
Market discipline	3.885***	4.649***	4.974***	4.932***
Contagion dummy	6.834***	5.956***	6.086***	6.348***
Inflation	0.000			
Per capita GDP (logs)	0.129			
Share of domestic credit in GDP (logs)	0.496			
Concentration (Herfindahl)		5.136**		
Deviation of stock prices from their fundamental value			4.965***	
Wholesale liabilities (share)				0.163***
Intercept	−6. 068	−5.709***	−5.469***	−5.809***
Number of obs.	29,155	29,862	29,862	27,800
Pseudo $R-$sq.	0.613	0.490	0.485	0.506
Log likelihood	−166.7	−279.3	−282.3	−211.6

*, **, and *** indicate significance at 10, 5, and 1% levels, respectively.

baseline model by introducing the ratio of stock indices for 222 EU banks relative to the FTSE-100 (Financial Times Stock Exchange) market index.[23] A plausible hypothesis is that, if a bank stock deviates substantially from the general stock market trend in 1 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 III) 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.

Finally, 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 (Huang and Ratnovski 2010). 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 our analysis (column IV) confirm that banks relying more heavily on wholesale financing are

[23] 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 zero 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.

more likely to experience financial distress than those banks that are mostly financed by retail depositors.

The impact of variables entering the baseline specification is qualitatively identical across models I–IV in Table 4 (except for the impact of capitalization in model I). This provides further indication of robustness of the baseline model.

4.4 Are bank risks converging across EU countries?

To test whether bank risks are converging across EU countries, two types of random effects models are estimated (see Table 5): one in which the intercept varies at the individual bank level (column I) and one in which the intercept varies at the country level (column II).[24] In economic terms, model (I) 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 (I), implying remaining heterogeneity across banks in terms of risk 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 (II), 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 (I) and (II) produce qualitatively similar results for the key financial indicators compared with the pooled specification (I) in Table 3. These results suggest that the main difference comes from the heterogeneity of intercepts, rather than the heterogeneity of slope coefficients.

These findings lend some support for establishing common benchmark criteria for banking sectors across the EU countries, as advocated in the recent initiative by the EU Commission (De Larosiere 2009). This is not to say that the convergence of bank risks within the EU is complete. The estimation results (Table 3) suggest that there are slight differences in the convergence of risks across countries and different types of financial institutions. For example, there are slight differences between German banks and those in the rest of EU. When Germany is excluded from the sample, the impact of asset quality becomes insignificant, but all other coefficients remain unchanged both in terms of statistical significant and qualitative impact. Also, for commercial banks, the impact of bank capitalization seems to be less important compared to the other organizational types, and commercial banks are more affected by the impact of liquidity risks. These results may be driven by the fact that commercial banks are more dependent on deposits as their main funding source, and the market discipline imposed by depositors makes liquidity management highly relevant for this organizational type of banks. Nonetheless, despite these caveats, the above findings provide important evidence of the convergence in bank risks among EU banks.

4.5 Predictive performance of the model

An important property of the logistic model is its precision in terms of minimizing Type I and Type II errors (Persons 1999). 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

[24] Panel data estimation results can also be considered as yet another exercise to examine robustness of the baseline model with respect to the estimation method.

Table 5 Panel data analysis of the baseline model. R-squared for the random effects (RE) model is calculated using McFadden's likelihood ratio

Models	(I) Random intercept at bank level	(II) Random intercept at country level
Capitalization	−37.059***	−29.239***
Asset quality	29.513***	19.368**
Managerial quality	0.119	0.121*
Earnings	−2.360**	−2.125***
Liquidity	0.886	0.600
Market discipline	7.724***	5.082***
Contagion dummy	8.756***	6.388***
Random error (log of st. dev.)	2.077***	0.263
Number of obs.	29,862	29,862
Pseudo R−sq.	0.487	0.520
Log likelihood	−247.8	−282.1

*, **, and *** indicate significance at 10, 5, and 1% levels, respectively.

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%). The table shows that the model correctly classifies 44 out of 79 distress events (55.7%), and 29,706 out of 29,783 non-distress events (99.7%) for the 10% 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, despite of its parsimoniousness, the model performs satisfactorily in classifying distressed banks and its discriminatory power is comparable to results reported in previous studies (see, e.g., Mannasoo and Mayes 2009) (Table 6).

Lowering the cutoff point to 1% 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% results in an even larger increase in the number of the Type II errors, while leaving Type I errors basically unchanged. Despite of this trade-off between Type I and

Table 6 Type I and type II errors

		Actual distress		
		Yes	No	Total
Cutoff point: PD=10%				
Classified distress	Yes	44	77	121
	No	35	29,706	29,741
	Total	79	29,783	29,862
Cutoff point: PD=1%				
Classified distress	Yes	50	258	308
	No	29	29,525	29,554
	Total	79	29,783	29,862
Cutoff point: PD=0.5%				
Classified distress	Yes	54	417	471
	No	25	29,366	29,391
	Total	79	29,783	29,862

Type II errors, the area under receiver operating characteristic curve (Fig. 2) exceeds 95%, which confirms high discriminatory power of the model.

4.6 Marginal effects

The coefficients of the logit model presented in Tables 3, 4 and 5 measure the direction of the impact but cannot be given an economic interpretation since the magnitude of the impact depends on the initial values of independent variables and their coefficients. A common approach to derive economic impact of individual financial ratios is to compute the marginal impact at the sample mean, as shown in Fig. 3. 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. Comparison of marginal effects across these three determinants of bank distress suggests that bank PDs are somewhat more responsive to changes in asset quality and earnings relative to changes in

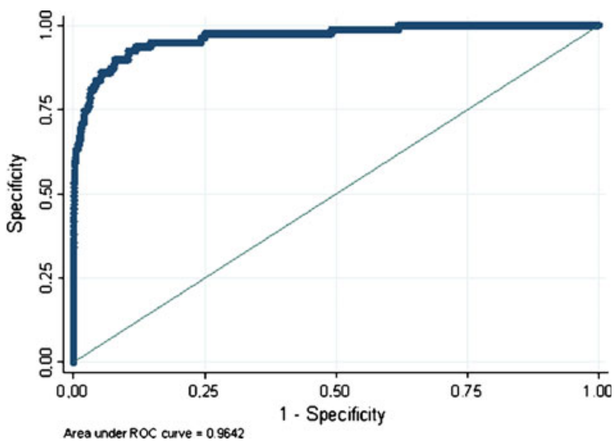
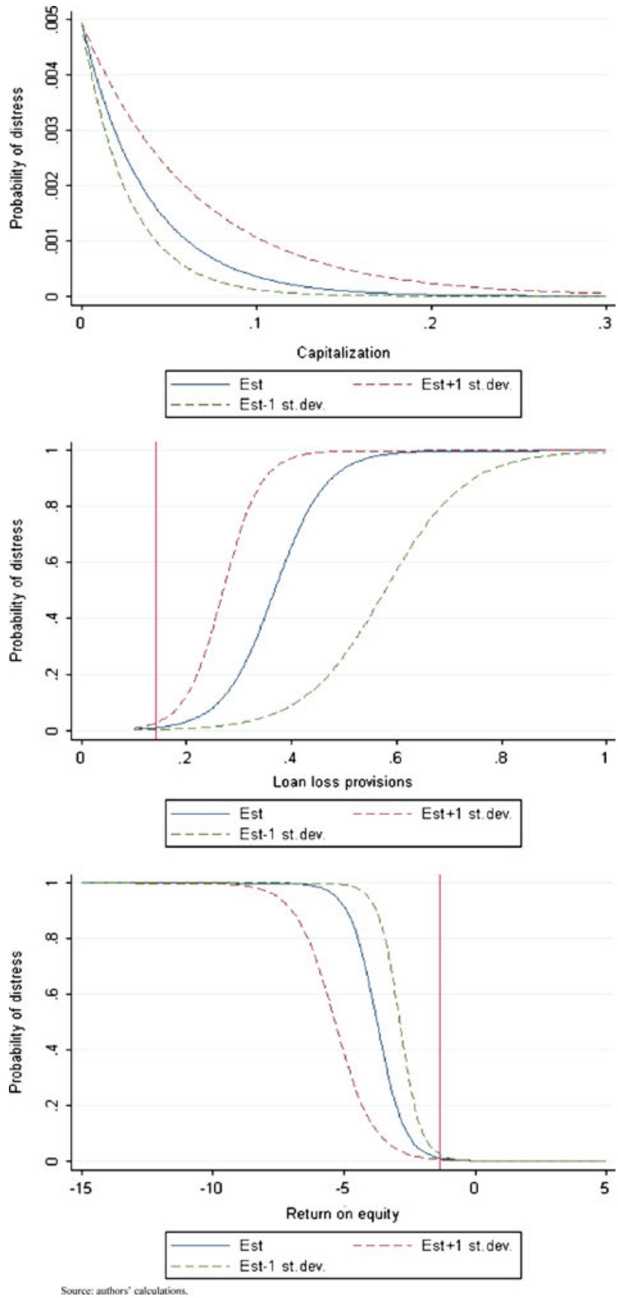


Fig. 2 Receiver Operating Characteristic (ROC). *Sensitivity* is the ratio of correctly predicted distress to all distress events (1-Type I error), and *specificity* is the ratio of correctly predicted sound banks to all sound banks (1-Type II error). The larger is the area under ROC, the higher is the predictive fit of the model

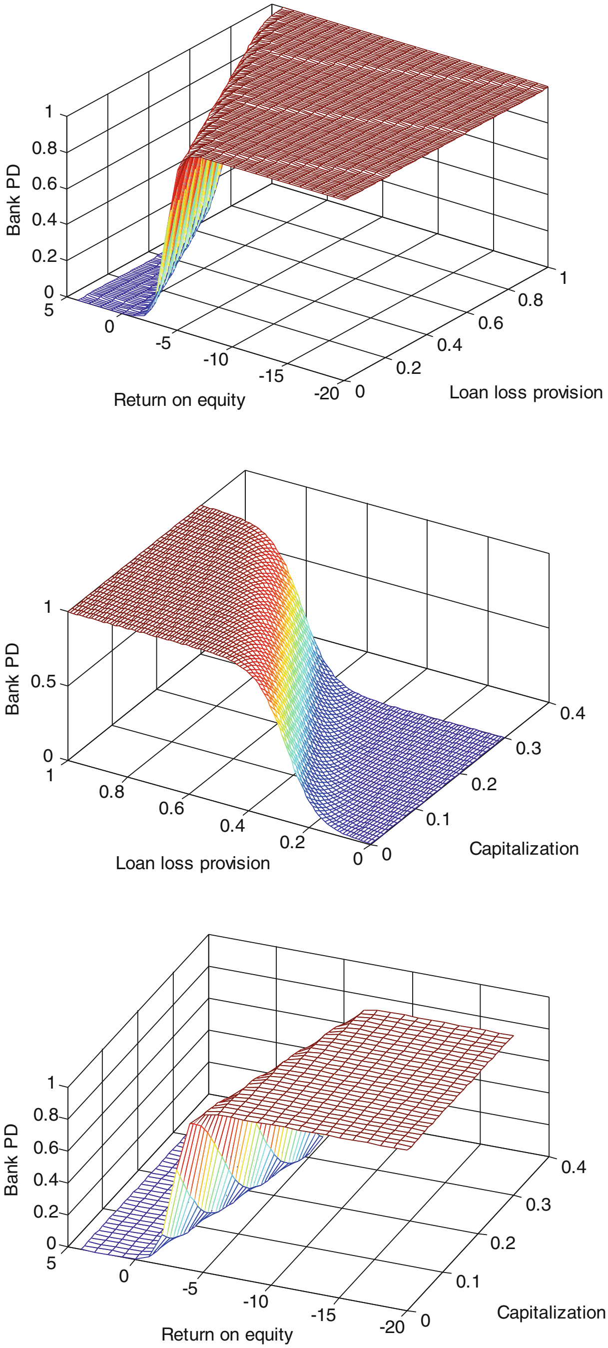
Fig. 3 Marginal effects of significant CAMEL covariates. Source: authors' calculations



capitalization. This finding highlights the importance of asset quality and earnings next to bank capitalization for early identification of weak banks.

Figure 4 shows the marginal impact of various pairs 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

Fig. 4 Trade-off in the impact on PD (pairs of significant CAMEL covariates). Source: authors' calculations



Source: authors' calculations.

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. The existence of the trade-off suggests that in designing new system of financial regulation in the EU, policymakers should undertake a systemic approach and consider not only capitalization, but also other important predictors of bank distress, such as asset quality and earnings.

5 Conclusions

This paper presents novel empirical evidence on the determinants of bank distress in the EU as a whole using a unique data set on bank distress. The evidence supports the notion that recent financial integration policies in the EU have led to convergence of bank risks across EU members, and and provides some empirical justification for introducing a more centralized system of financial regulation in the EU.

We scrutinize the importance of capitalization and market discipline as two main pillars of the Basel II Accord. We find a significant effect of capitalization on bank distress, but its economic impact is lower than the impact of asset quality and earnings. We advocate that these two variables should be taken into account in addition to bank capitalization when designing pan-European benchmarks of sound banking conduct. We also find solid evidence on the importance of market discipline in the EU banking, on the side of both depositors and financial market participants. This finding justifies the importance of transparency and dissemination of information for more efficient EU-wide banking regulation.

Among other results, we provide empirical evidence suggesting the importance of contagion effects in the EU banking. Furthermore, in line with the concentration-fragility view, we show that banks operating in more concentrated banking sectors are more likely to experience bank distress relative to banks operating in less concentrated markets. Lastly, we show that bank hazards increase with higher share of wholesale funding, in line with recent theoretical models emphasizing the role of wholesale funding for bank distress.

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 our understanding of the main factors influencing soundness of banks.

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