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BANK FAILURES IN EUROPE DURING THE FINANCIAL CRISIS

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ABSTRACT

We assemble a new data set on bank failures, bailout with public finances, in the European Union (E.U.), in the wake of the on-going financial crisis. Our model is estimated with data on 444 commercial banks from 19 countries in Europe over 2004-2010, which yields a sample of 1,504 unbalanced panel observations. Results show that bank failures were critically determined by financial accounting information and macroeconomic conditions, and that macroeconomic information improves the forecasting ability of our model over and above financial accounting information. The predictors from our model can be used by monetary authorities to predict bank failures, and the probabilities to assess pressure in the banking sector, the pricing of credit, and their derivatives. Our findings are consistent with recent regulatory impositions in the Basel setting that require banks to hold higher capital levels and lower risks.

Keywords: Financial crisis; Banks; Default; Government bailouts

JEL Classification: G01, G20, H81

RESUMO

Reunimos um conjunto de dados recentes sobre bancos com eventos de incumprimento e de resgate financeiro estatal, na União Europeia (U.E.), no contexto da actual crise financeira. O modelo foi estimado com dados de 444 bancos comerciais de 19 países da U.E. para o período de 2005-2010, o que produziu uma amostra de 1.504 observações, em painel não balanceado. Os resultados mostram que os eventos de incumprimento e resgate nos bancos considerados foram significativamente influenciados pelos seus dados contabilísticos e pelas condições macroeconómicas do país de origem, sendo que os dados macroeconómicos aumentam a capacidade de previsão do modelo muito além dos dados contabilísticos. As variáveis explicativas do nosso modelo podem ser usadas pelas autoridades monetárias a nível mundial para prever eventos de incumprimento de bancos e avaliar eventuais pressões no sector financeiro resultantes das políticas de crédito. Os nossos resultados são consistentes com as recentes imposições regulamentares de Basileia, que exigem que os bancos mantenham níveis mais altos de capital e níveis de risco mais baixos.

Palavras-chave: Crise financeira; Banca; Incumprimento; Resgate financeiro estatal.

Classificação JEL: G01, G20, H81

CONTENTS

1 SUMÁRIO EXECUTIVO

A literatura na área de finanças e contabilidade tem dado um significativo contributo na análise da falência ou das dificuldades financeiras de empresas. A falência de bancos, contudo, não acompanhou essa tendência. No entanto, a recente crise financeira, fortemente marcada por dificuldades no setor financeiro, colocou esta temática no topo das preocupações das autoridades monetárias e políticas. A falência da Lehman Brothers, em 2008, nos Estados Unidos, foi um importante ponto de viragem para esta preocupação.

Na União Europeia (U.E.), as autoridades viram-se forçadas a implementar e reforçar as medidas de apoio e resgate financeiro estatal ao setor financeiro. A Comissão Europeia estabeleceu como medidas de apoio a atribuição de garantias governamentais, programas de recapitalização, criação de um regime de "*bad bank*" e nacionalizações.

Os Acordos de Basileia, do Banco de Pagamentos Internacionais (*Bank of International Settlements* – BIS), foram estabelecidos para definir requisitos mínimos de capital para as instituições bancárias, estabelecendo um mínimo de 8% para o rácio de capital. A crise financeira mostrou contudo que diversos bancos com rácios de capital acima do mínimo indicado foram alvo de resgates financeiros.

As referências de literatura em matéria de risco de crédito e de falência de empresas utilizam como modelo os dados financeiros e contabilísticos dessas empresas, uma vez que estes dados permitem obter uma visão apropriada da situação financeira. Mas o contexto macroeconómico tem também uma significativa influência no desempenho financeiro das empresas e em especial das instituições financeiras.

Tendo como base o contexto descrito, este estudo procura analisar a capacidade de um conjunto de variáveis contabilísticas e macroeconómicas em prever a necessidade dos apoios e resgates financeiros a instituições financeiras, ocorridos na U.E. no período entre 2005 e 2010.

Para esta análise foram recolhidos dados sobre os resgates e apoios financeiros atribuídos pela U.E. durante o período em análise, no sítio de internet da Comissão Europeia. No referido período foram considerados programas de apoio e resgate financeiro atribuídos a 53 bancos de 13 países da U.E., sendo França o país com mais bancos resgatados, seguida da Grécia e da Holanda. A variável dependente considerada (FAIL) é uma variável binária que apresenta o valor 1 quando o banco foi alvo de um programa de apoio e resgate financeiro, e 0 caso contrário, seguindo a metodologia de Jin *et al.* (2011) e de Chava and Jarrow (2004).

Para as variáveis explicativas foram recolhidos dados contabilísticos na base de dados *Bankscope* (*Bureau Van Dijk*), sobre 444 bancos comerciais de 19 países da U.E. para o período de 2005 a 2010, de onde resultou uma amostra, em painel não balanceado, de 1.504 observações. Os rácios financeiros considerados na análise avaliam aspetos como a qualidade dos ativos, os níveis de capital, o desempenho operacional e os níveis de liquidez dos bancos. Relativamente às variáveis macroeconómicas, foram recolhidos dados nos sítios de internet do Eurostat e do Banco Mundial, considerando indicadores relativos ao país de origem dos bancos considerados na análise. As variáveis macroeconómicas consideram aspetos como o desempenho económico do país, os níveis de endividamento a nível governamental e medidas de avaliação do mercado de crédito.

Para a estimação do modelo em análise foi utilizada uma regressão logit, que é a mais indicada para modelos de variável dependente binária. Os resultados obtidos revelam que a conjugação de variáveis contabilísticas e macroeconómicas é crítica para a perceção das probabilidades de incumprimento dos bancos. Foi ainda possível concluir que a introdução das variáveis macroeconómicas no modelo estimado melhora significativamente o seu poder de previsão.

Este estudo contribui assim para uma melhor compreensão das causas e consequências da atual crise financeira na situação financeira dos bancos. Esta poderá por isso ser uma importante ferramenta a considerar pelas autoridades de supervisão bancária na avaliação dos bancos.

2 INTRODUCTION

The analysis of corporate failure, bankruptcy and default, has a long tradition in accounting and finance (see, among many others, Dimitras et.al., 1996; Westgaard and Wijst, 2001). There are very few known incidences of bank failures in Europe. A notable example, which precipitated the first Basel Capital Accord, is the failure of Hestatt Bank in Germany. Other isolated examples include the failures of BCCI and Baring Brothers. With few exceptions, but largely focused on the incidences of failure over time in the U.S. (see, among others, Kumar and Ravi, 2007), the analysis of bank failures in Europe has received little attention. The recent collapse of Lehman Brothers in the U.S. in 2008, followed by the Royal Bank of Scotland in the U.K. and several other banks in Europe, placed the analysis of bank failures, insolvency and bailout, high on the agenda of monetary and political authorities around the world. Monetary authorities are concerned about the disruption of the good functioning of financial markets and supply of credit to the economy, while political authorities, confronted by mounting public pressure, are concerned about the cost of bailouts, and its consequent impact on budget deficits and taxpayers.

Following the incidences of failure in the U.S. and Europe with their perverse effects on the functioning of interbank markets, and the inception of the global financial crisis, many governments have had to bail out banks with public finances. In this paper, we use this unique natural experiment, to study the factors that determined the bailout of banks with public finances, which we designate as bank failures. An alternative definition of failure could be based on the widely-known minimum capital requirement ratio of 8% for banks decreed by the Bank for International Settlements. The recent evidence however shows that several banks with capital ratios above the minimum were bailed out with public finances. Notable examples include the BNP Paribas and Commerzbank, which reported capital ratios well above the minimum on the eve of their bailout.

The recent bank failures resemble corporate failures, although with notable qualifications that hinge on the critical importance of banks and the need to supervise and regulate their activity to ensure the soundness of the functioning of modern financial markets (Benston *et al.*, 1986). Corporate failure is defined as the probability that a borrower will fail to repay an amount owed to its lender (BCBS, 2005a). Bank failures, which we study in this paper and is less frequently studied in the accounting and the finance literatures, is defined as the probability that a bank will be bailed out with public finances; following both early (see, among others, Martin, 1977; Thomson, 1991) and recent (Jin *et al.*, 2011; Shaffer, 2012) studies in the U.S. context, we define this as failure.

To the best of our knowledge, our study is among the very few to develop a model of failures for European banks in the context of the recent financial crisis.[1] In a related study, Poghoshyan and Cihak (2011) analyze bank distress in a large sample of banks based in the European Union (E.U.). They show that financial accounting, market and contagion effects critically determined the distress of banks between 1996 and 2007. The failure model developed in this paper resembles, it is identical but not similar, to credit risk models for banks produced by independent rating agencies for their clients. Credit risk models also rely on financial ratios and macroeconomic conditions to predict default of debt securities issued by borrowers, who are clients of rating agencies. These credit risk models are often subject to the classic conflict of interest between rating entities (providers) and debt issuers (their clients), which inhibits the correct adjustment of their evaluations (see, among many others, Saunders and Allen, 2010).

In this paper, we question whether financial accounting and macroeconomic indicators could have predicted the eventual bailout of banks in the aftermath of the inception of the global financial crisis. To answer our question, we assemble a new data set on bank failures in the European Union (EU). Our data set comprises information on 444 commercial banks from 19 EU countries over the 2005-2010 period, yielding a sample of 1,504 unbalanced panel observations. We follow a methodology whereby we estimate a model with financial ratios and macroeconomic information and ascertain the incremental predictive ability of macroeconomic conditions, considered a key to the driver of the financial crisis by many economists, over and above financial accounting information.

The predictors of the eventual bailouts can be used as early warning signals to predict future bank failures by monetary authorities, and the bailout probabilities can be used to assess pressure in the banking sector and the consequent capital provisioning required to avoid bank failures and for pricing debt and their derivatives. At a broader level, our study

[1] Failure of European banks has been far less studied. In a study related to ours, Ötker-Robe and Podpiera (2010) show that credit default swap (CDS) spreads of 29 large complex financial institutions in Europe from 2006 to 2008 were critically determined by financial ratios such as performance, the cost to income revenues and the degree of income diversification as well as the macroeconomic conditions. Along a similar line, Uhde and Heimeshoff (2009) show that the Z-score (return on average assets plus the equity to total assets, to the standard deviation of the return on average assets), a measure of the capacity to absorb shocks under adverse conditions, over 1997-2005 were critically determined by macroeconomic conditions such as the gross domestic product (GDP) and the rate of growth of credit.

casts light on the on-going debate on the causes and consequences of the financial crisis and draws lessons that can help prevent future bank failures with public finances.

The paper is structured as follows: we review the literature that forms the basis of models for predicting bank failure in section 2; we detail the data sources and the empirical framework in section 3; we report the key findings in section 4; and summarize and conclude the paper in section 5.

3 DETERMINANTS OF BANK FAILURES IN EUROPE

The Basel Capital Accords are intimately related to bank failure events in Europe. The Basel Committee on Banking Supervision (BCBS), based in Basel, and functioning under the aegis of the Bank for International Settlements, was formed in response to the failure of the Herstatt Bank from Germany in 1974. Basel I, instituted in 1988 (BCBS, 1988), required banks operating at an international level to have a minimum capital of 8% of their risk-weighted assets. The standard risk weight categories based on the solvability and liquidity of borrowers used under Basel I were 0% for sovereign debt, 20% for exposures to OECD Banks, 50% for residential mortgages and 100% weighting for consumer loans and unsecured corporate debt.

Basel II, approved in 2004 (BCBS, 2005b), required banks to put aside sufficient capital to safeguard themselves against macroeconomic downturns, market, credit and operational risks. Within this revised framework, the standardized approach, among other approaches outlined in the framework, set the risk weights for different types of credit risk. Basel II introduced a 150% weighting for debt with low credit ratings. The minimum capital required remained at 8% of risk-weighted assets of Tier I (at least 4% in common equity and at least 2% in disclosed reserves) and Tier II (secondary capital, undisclosed reserves, general loss reserves, hybrid instruments, revaluation reserves, subordinated debt, and more). Supporters of this revised framework believed that it could immunize the international financial system from the failure of a major bank or a series of banks interconnected via the interbank market. However, this did not prove to be the case as the recent failure of a number of banks showed.

Basel III (BCBS, 2010a; BCBS, 2011) was instituted following the initiation of the on-going crisis that led to the collapse of Lehman Brothers and subsequently to the bailout of several banks around the world, but more importantly in Europe. It requires banks to hold 4.5% of common equity and 6% of Tier I capital of risk-weighted assets. This framework brought about the additional requirement for capital buffers, an obligatory capital conservation buffer of 2.5% and an optional countercyclical buffer, which allows national regulators to require up to a further 2.5% of capital during periods of high credit growth. In addition, it introduced a minimum 3% leverage ratio and the liquidity coverage ratio which requires banks to hold sufficient high-quality liquid assets to cover its total net cash outflows over 30 days, and the net stable funding ratio which requires the available amount of stable funding to exceed the required amount of stable funding over a one-year period of extended stress.

The Basel Capital Accords signal the critical importance of accounting and macroeconomic factors in avoiding bank failures. Financial ratios computed from accounting statements, which need to be filed with supervisors, regulators, public and tax authorities, and are fundamental for monitoring purposes, reflect the true and fair view of the financial standing of banks. Macroeconomic conditions can anticipate or postpone failure. In particular, economic downturns, such as the on-going crisis in Europe, can push banks to failure; and economic upturns can allow banks to put aside capital to cushion against periods of economic downturn.

A problem with financial ratios based on accounting statements and macroeconomic indicators is that there are many ratios and indicators that can influence failure. The sparse literature on bank failures has yet to reach agreement on which ratios and indicators can best predict failure (see, among others, Kumar and Ravi, 2007). In the absence of agreement on which financial ratios and macroeconomic can best predict the eventual failure of banks, and the need to be parsimonious, we build on the Basel Capital Accords and the existing literature to hypothesize (H) the influence, with one-period lag, of accounting ratios (H1) representing the asset quality (H1a), capital (H1b), performance (H1c), and liquidity (H1d), of banks; macroeconomic conditions (H2) representing growth in the domestic product (H2a), inflation (H2b), public deficit (H2c), public debt (H2d) and private credit flow (H2e); and an indicator of information available in private and public registries on the credit extended by banks (H3).[2]

In terms of asset quality, we assess the influence of loan loss provisions to net interest revenue (LLP_NIR, H1a.1) and loan loss reserves to impaired loans (LLR_IL, H1a.2), on failure. Larger values in LLP_NIR reflect poor loan quality and a higher probability of default of borrowers to whom banks lend money and consequently higher probability of failure of banks. Notwithstanding, a high level in LLP can also indicate conservatism of bank managers in recognizing potential loan losses (see also Jin *et al.* (2011) in the context of failure of U.S. banks). We thus do not *a priori* assign a sign to the

[2] The CAMELS in the U.S. also considers financial ratios - asset quality, capital, performance and liquidity, sensitivity to market conditions and qualitative factors related to management quality. The BCBS (2005a, par. 8; 2006, par. 1; 2010b, par. 38) points the need to have sound corporate governance systems in place to maintain public trust and confidence in the functioning of modern financial systems.

relationship between LLP_NIR and bank failures in Europe (H1a.1). The ratio of loan loss reserves to impaired loans ratio (LLR_IL) measures the monetary cushion that banks possess to withstand loan impairment. The higher this ratio, the more protected those loans are in case of default by borrowers, transmitting a better asset quality (see also Jin *et al.* (2011)). We thus expect a negative relationship between LLR_IL and bank failures in Europe (H1a.2).

In terms of capital, we assess the influence of the equity to total assets (EQ_TA, H1b.1) and the Z-score (ROAA, return on average assets, plus the equity to total assets, to the standard deviation of the ROAA, H1b.2). EQ_TA measures the extent to which banks' assets are financed by equity. This ratio can be used to evaluate the strength of the balance sheet, as it is expected that the higher this ratio is, the higher the solidity to withstand losses, thereby demonstrating a lower probability of failure (see also Shaffer, 2012 – U.S.). We thus expect a negative relationship between EQ_TA and failure of banks (H1b.1). The Z-score measures the level of capitalization and indicates banks' muscle to absorb shocks under adverse conditions. The Z-score increases with profitability, and consequently increases the capital, and decreases with increasing level of the standard deviation of returns (Uhde and Heimeshoff, 2009). We expect a negative relation between the Z-score and failure (H1b.2).

In terms of performance, we assess the influence of two measures of operational performance, the return on average assets (ROAA) and the cost to income ratio (CIR), on bank failure. ROAA measures the operational performance of banks by weighing the earnings with respect to assets. We expect that the larger the ROAA, the lower the probability of failure (H1c.1), as ROAA indicates better operational performance and higher resilience to shocks (Ötker-Robe and Podpiera, 2010). CIR measures the level of overheads as a percentage of income before provisions. Significant costs of running the bank can lead to lower levels of efficiency, which can reduce the soundness of banks. As a result, we expect a positive relation between CIR and the failure of banks in Europe (H1c.2).

Finally, we assess the influence of liquidity, the interbank ratio (IBR) and the ratio of net loans to total assets (NL_TA), on failure. IBR measures the level of loans to other banks as a percentage of the money borrowed from other banks, showing that the higher this ratio is, the higher the bank's liquidity. We thus expect a negative relationship between IBR and bank failures in Europe (H1d.1). NL_TA indicates the weight of loans in the assets. Higher levels in this ratio represent a lower level of liquidity, which leads to higher levels of dependence on non-liquid assets, increasing the risk of bank failure. We thus expect a negative relationship between NL_TA and bank failures in Europe (H1d.2).

In addition to financial ratios, the macroeconomic dynamics can also influence bank failure in Europe. We assess the influence of the growth rate of GDP (GDP_GR; H2a), and the inflation rate (HICP, H2b) of the country where the bank is headquartered as the main indicators of economic dynamics. We expect higher levels of the GDP growth rate to postpone bank failures in Europe (H2a). We expect higher levels of inflation to increase the ambiguity over economic prospects of the country and thereby discourage capital expenditure plans of entrepreneurs. We thus foresee a negative relationship between the inflation rate and failure (H2b). The governmental budget surplus/deficit, measured as a percentage of GDP at current market prices (BUD_DEF), and gross public debt, also measured as a percentage of GDP at current market prices (PUB_DEBT) not only indicate expansionary public choices that improve business prospects for banks but also point towards potential pressures on domestic banks to finance budget deficit and public debt. We thus do not assign any sign *a priori* to the influence of BUD_DEF (H2c) and PUB_DEBT (H2d) on bank failures in Europe. The liabilities of the private sector as a percentage of GDP (PCREDITF) indicate the pressure in the credit market. The larger the amount of the private sector' liabilities, the greater the potential for default, and consequently for bank failures. We thus expect a positive relationship between PCREDITF and bank failures in Europe (H2d).

In addition to financial ratios and macroeconomic indicators, we use a qualitative index that measures the depth of information to assess credit available in private and public registries (CDINFO). The index rates the quality and accessibility of information on credit on a scale of 0-6, with higher values indicating the availability of more credit information to facilitate lending decisions. We thus expect a negative relationship between CDINFO and bank failures in Europe (H3).

4 DATA AND METHOD

4.1 Sample

The data set used in this study relates to commercial banks operating in the E.U. during the 2005-2010 period. It includes financial ratios relating to asset quality, capital, performance and liquidity, macroeconomic indicators and qualitative information. In our analysis, the explanatory variables are lagged by one year. Our data on financial ratios were collected from Bankscope (Bureau Van Dijk), considering consolidated data; data on macroeconomic indicators on the countries in which banks have their headquarters were collected from the Eurostat, and data on qualitative indicators were collected from the World Bank.

Failure events, public bailouts of banks, were obtained from the European Commission (E.C.), by constructing an original database with information from publications related to state aid measures, in the Official Journal of the European Union. Public bailout of banks in the E.U. during the financial crisis encompassed government guarantees, recapitalization programs, creation of a bad banks regime (involving special conditions to reimburse creditors), and nationalization. Banks in the sample benefited simultaneously from different bailout programs making the identification of one single program difficult (Sutton *et al.*, 2010). For this reason we identify the banks that failed as those which received at least one of the referred types of public bailout. The variable takes the value 1 if a failure event occurred within the period (considering the occurring year and the subsequent years), and takes the value 0 otherwise.

In Table 1 we summarize the sample of banks and the number of banks with failure events considered, by country of origin and by year. Our initial sample included 13,783 observations, relating to 1,969 commercial banks from the 27 E.U. countries. Following the qualitative evaluation of the information and the exclusion of banks with missing observations, we were left with a sample of 1,504 usable bank-year observations on 444 commercial banks from 19 EU countries over 2005-2010. In our sample, 53 banks from 13 countries were bailed out, or failed. Before 2008, only 2 banks were bailed out, one in Czech Republic, and another in Germany. In 2008, 31 banks were bailed out, and in 2009 a further 13 banks were bailed out. France registered the largest number of bailouts (10 of its 71 banks considered in the sample), followed by Greece with 8 banks and Netherlands with 7 banks (these countries are represented with a total of 14each). The banks from 6 countries, Denmark, Finland, Poland, Slovakia, Spain and Sweden, were not bailed out between 2005 and 2010.

4.2 Description and descriptive statistics

In Table 2 we describe our variables and their descriptive statistics. Our dependent variable (FAIL) indicates the occurrence of failure events, bailout, in the abovementioned sample.

In terms of our independent variables – financial ratios, LLP_NIR has an average of 23.297% (27.380% for failed banks and 22.586% for non-failed banks). This percentage varied between 8.474% and 49.268% during the sample period. LLR_IL has an average of 98.542% (81.138% for failed banks, and 101.571% for non-failed banks), which indicates that, in average, banks created reserves slightly below the amount of impaired loans, deteriorating from 152.248% and 73.885% during the sampled period with the latter figure reported following the onset of the financial crisis. The EQ_TA has an average of 7.996% (5.221%, for failed banks and 8.479% for non-failed banks). The ZSCORE has an average 47.946 (15.675 for failed banks, and 53.564 for non-failed banks). The average ROAA during the sampled period was 0.605% (0.406%, for failed banks and 0.640% for non-failed banks), deteriorating from 0.906% to 0.079% after the onset of the financial crisis. The average CIR remained relatively stable 64.678% (66.459% for failed banks and 64.368% for non-failed banks) during the sampled period. IBR averaged 130.561% (78.787% for failed banks and 139.574% for non-failed banks). The NL_TA had an average of 61.154% (56.425% for failed banks and 61.977% for non-failed banks).

In terms of our independent variables – macroeconomic variables, the statistics show that the average growth rate of GDP in the sample countries was 1.751% varying during the sampled period between -4.421% (in 2009) and 4.189% (in 2006). Comparing countries with failed banks and countries without, the former group registered an average GDP of 1.110% and the latter group an average of 2.285%, showing a more difficult macroeconomic context in countries with failed banks. Countries such as France with 10 bank failures experienced an average growth rate of 1.050%; and Netherlands, with 7 bank failures experienced 1.633%; all below average for the set of countries in our sample. The statistics also show that the average HICP was 2.417% varying between 0.911% (in 2009) and 3.811% (in 2008). The average BUD_DEF was -2.450% (-3.726% in countries with failed banks and -1.387%

in countries without failed banks). Greece had the highest deficit -15.800% followed by Ireland with -14.200%, both following the onset of the financial crisis. PUB_DEBT averaged 56.535% (68.672% in countries with failed banks and 46.420% in countries without failed banks). Greece had the largest percentage of public debt as a percentage of GDP, 129.300% in 2009. Luxembourg had 6.700% in 2006 and 2007.

In terms of our independent variables – qualitative variable, the statistics for the depth of information index (CDINFO) shows that Luxembourg had the lowest index (0), i.e. the lowest quality and accessibility of information on credit in private and public registries, and Austria, Germany, Great Britain and Italy have the highest index (6), i.e. the highest quality and accessibility of information on credit in private and public registries.

In Table 3 we report the correlations among our variables. In general, the explanatory variables do not show significantly high correlations so as to cause multicollinearity in model estimation.

4.3 Method

The method used in this paper involves the specification of an empirical model, the estimation of coefficients, and testing whether or not the sign and significance of the coefficients lead to rejecting the hypotheses. The requisite to model bank failure with a binary dependent variable precludes the use of the ordinary regression analysis. Canbas *et al.* (2005 – 21 banks in Turkey between 1997 and 2003), Martin (1977 – 58 banks in the U.S. between 1970 and 1976), Whalen and Thomson (1988 – 58 banks between 1983 and 1986 in the U.S.) and Thomson (1991 – 770 banks between 1984 and 1989 in the U.S.) deploy the logistic model to estimate models of bank failure.

A particular feature of the logistic model is that it is linear in the log-odds and this makes the coefficients and their odds ratios more straightforward to interpret than those of its closest alternative, the probabilistic model. The logistic (and also the probabilistic) model accommodates the possibility of a bank that fails in a particular year to continue as failed in subsequent years until overcoming its status. In this sense, like previous studies, we pool our data. If observations were independent from one year to another, then the basic structure of the logistic model would have to be adapted to incorporate the assumption of independence of irrelevant alternatives.

If data on the time to failure were assembled, then the Cox proportional hazard model could be estimated as an alternative to the logistic regressions estimated in this paper (see also Lane *et al.*, 1986 – N.A.; Whalen, 1991 – 1,500 U.S. banks in 1987-90). Lee and Urrutia (1996) contend that logistic regression analysis and the proportional hazard model are identical.

The requirement of results of failure in terms of testing hypotheses for determining early warning signals of bank failure and producing probabilities of failure for assessing pressure in the banking sector impede the use of the other closest alternatives such as multivariate discriminant analysis (Kao and Liu, 2004 – 24 Taiwanese banks in 2000), data envelopment analysis (Barr *et al.*, 1994 – 930 U.S. banks in 1984-87), neural networks (Alam *et al.*, 2000 – 100 U.S. banks in 1991; Bell, 1997 – 2,067 U.S. banks in 1985-86; Tam and Kiang, 1992 – 202 U.S. banks in 1985-87), or multicriteria decision-making (Olmeda and Fernandez, 1997 – 66 Spanish banks in 1977-85), because these only produce probabilities as opposed to outcomes in terms of predictors.

We use the data described above to estimate a logistic model for the probability of a bank requiring a bailout, failure. The logistic model formulated here contains a binary dependent variable (1=FAILURE, 0=NON-FAILURE). The independent variables are the financial ratios, macroeconomic indicators and qualitative information, with one-period lag from the failure events. The model is estimated using STATA, under a procedure that estimates a binary logistic model via maximum likelihood. Failure probabilities are produced for the overall model. In formal terms, the model tested in this study is:

$$Fail_{it+1} = \alpha + \beta_{it} \text{ Financial ratios} + \beta_{it} \text{ Macroeconomic variables} + \beta_{it} \text{ Qualitative information} + \varepsilon_{it}$$

where the i and t subscripts represent bank and year, respectively, α is a constant, β's are the parameters to be estimated, and ε_{it} is an error term. The model is estimated using the random effects logistic regression procedure, appropriate for our unbalanced panel.

5 FINDINGS

5.1 Baseline model

We present the results relating to the estimation of our model in Panel A of Table 4, denoted hereafter as the baseline. We report failure rates in deciles in Panel B of Table 4 and the classification errors in Panel C of Table 4.

Amongst other relevant information, Table 4 contains coefficient estimates, odds ratios and standard errors. Odds ratios are more informative than coefficient estimates because the former gauge the probability of failure with respect to the probability of non-failure. For binary independent variables, the odds ratio specifies the predicted odds of the independent variable (ascribed 1) with respect to the remaining category (ascribed 0); multiplying the odds by 100 gives percentage impact. For continuous variables, subtracting 1 from the odds ratio and multiplying by 100 gives the percentage change in the odds for each unit increase in the independent variable.

The findings from the estimation show that financial ratios and macroeconomic indicators determine failure of European banks. In terms of financial ratios, LLR_IL, EQ_TA, ROAA and IBR are negatively related to failure. A 1-unit increase in these variables reduces the odds of failure by 1.1%, 15.7%, 33.7% and 0.7%, respectively. These findings point towards the critical importance of the accounting-based regulatory framework under which European banks operate. We do not reject our hypotheses H1a.1, H1b.1, H1b.2 and H1c.1.

In terms of macroeconomic indicators, GDP and BUD_DEF are negatively related to failure. A 1-unit increase in these variables reduces the odds of failure by 26.2% and 19.2%. PCREDITF is positively related to failure. A 1-unit increase in this variable increases the odds of failure by 3%. These findings highlight the significant importance of the macroeconomic conditions in anticipating or postponing failure as the on-going crisis clearly demonstrated. We do not reject our hypotheses H2a, H2b, H2c and H2d.

Overall, our findings indicate that financial ratios alongside macroeconomic conditions can predict future failure of banks in Europe. In the subsection on robustness tests, we also show the incremental predictive ability of macroeconomic conditions in predicting failure of banks in Europe.

5.2 Predictive ability of the baseline model

In Panel B of Table 4 we show the findings on how effectively our baseline describes the dependent variable. Specifically, we ranked banks into deciles based on their estimated failure probabilities, placing banks with higher predicted failure probability into the first decile, the next most likely to fail in the second decile, and so on. Then, for each decile, we computed their failure probability by comparing the number of failures with the number of observations in each decile (Hosmer and Lemeshow, 2000). The first decile aggregates 36.800% of failures. The first two deciles show that the model can explain more than 50% of the failures. The bottom five deciles show that the model aggregates lower incorrect predictions to further attest to the predictive ability of our baseline model.

5.3 Classification Errors

In Panel C of Table 4 we show the findings on the two types of classification errors: if a bank that fails is wrongly classified as a non-failing bank (Type I), and, if a non-failing bank is wrongly classified as failing bank (Type II). For a cut-off value of 0.5, i.e., whereas over 50% are classified as failing, banks with a predicted probability below or equal to 50% are classified as non-failing, the model generates an overall correct classification of 91.760%. Reducing the cut-off to 0.06 decreases the number of times that a failing bank is incorrectly classified as a non-failing bank (Type I error). Using a cut-off level of 0.06 the model generated an overall correct classification of 59.640%, which is reasonable in this type of model. Using a cut-off level of 0.05 and 0.04 the model generated an overall correct classification of 54.920% and 49.340%, which again is reasonable in this type of model since we are not using artificially matched samples.

5.4 Robustness of the findings of the baseline model

The Basel Capital Accords rely critically on financial ratios and macroeconomic conditions in monitoring banks. So far we have built on this framework to hypothesize and test the influence of financial ratios and macroeconomic conditions predicted in the Accords. In this section, we perform several tests to verify robustness of our baseline specification; these are presented in Tables 5 to 8. The descriptive statistics and sources of the variables used for robustness tests are reported in Table 2 as are the variables used for the baseline.

We re-estimated the baseline specification of our model: a) without macroeconomic and qualitative indicators to assess their incremental predictive ability over and above financial ratios (Table 5, Panel A); b) with an indicator of whether the country has adopted the Euro (EURO, Table 5, Panel B); c) with an indicator of whether the bank adopts the international financial reporting standards (IFRS Table 5, Panel C); d) with an indicator of whether the bank is listed or not (LISTED, Table 5, Panel D); e) with an indicator of the role of government in the economy (GOV_ROLE, Table 6, Panel A); f) with an indicator of creditor rights (CREDITOR_RIGHTS, Table 6, Panel B); g) with an indicator of shareholder rights (SHAREHOLDER_RIGHTS, Table 6, Panel C); h) with an indicator of board size (BOARD_SIZE, Table 7, Panel A); i) with an indicator of board type, one-tier or two-tier structure (BOARD_TYPE, Table 7, Panel B); j) with an independence indicator (INDEP, Table 7, Panel C); k) with an indicator for the banks' total assets (SIZE, Table 8, Panel A); l) with an indicator of restrictions on banking activity (RESTRICT, Table 8, Panel B); and m) with an indicator of bank's total capital ratio (TCR, Table 8, Panel C), to assess their influence on bank failures in Europe.

In Table 5 we report the findings for the baseline with only financial ratios (Panel A). We deployed the likelihood ratio test to assess whether the model with financial ratios, macroeconomic and qualitative indicators, our baseline reported in Panel A of Table 4, fits significantly better than the model with just the financial ratios. This test indicates if the observed difference between the fit measures of both models (the log-likelihoods) is statistically significant. We first computed the -2 log-likelihood of the model without financial ratios (-288.406) and then with financial ratios, and macroeconomic and qualitative indicators (-265.384). Second, we computed the likelihood ratio statistic, the difference between the -2 log-likelihood of each model with and without the variable under study (46.044). We compared this difference with the critical value from the chi-squared distribution with 6 degree of freedom. Given that 46.044 exceeds the critical value of 22.458 at $p<0.001$, the null hypothesis that the two distributions are similar is rejected. We reject the null hypothesis that the observed values of our χ^2 have the same theoretical distribution. This allows us to conclude that statistically the model with macroeconomic and qualitative indicators has an incremental effect on our baseline model of default (at the 1% level of significance).

In Panel B of Table 5 we augment the baseline with the variable EURO, which captures whether the bank is headquartered in a country that has adopted the euro. The data were sourced from the European Commission (E.C.). The descriptive statistics in Table 2 point towards a higher failure rate of banks headquartered in countries that adopted the euro: the average for countries with failed banks is 0.809 compared to average for countries with non-failed banks that is0.633; this is confirmed by the positive and statistically significant (1% level) relationship between EURO and failure in the regression analysis. The predicted odds of failure of banks headquartered in countries that adopted the euro is 19.062% due to the sluggish macroeconomic conditions in Europe and the subsequent need for banks in the Eurozone to accommodate the debt crisis in Greece and Ireland early on at the inception of the financial crisis.

In Panel C of Table 5 we augment the baseline with the variable IFRS, which captures the adoption by banks of International Financial Reporting Standards. The data were sourced from the Bankscope. The descriptive statistics in Table 2 point towards a higher failure rate of banks that adopted the IFRS: 0.978 for failed banks and 0.751 for non-failed banks; this is confirmed by the positive and statistically significant (1% level) relationship between IFRS and failure in the regression analysis. The predicted odds of failure of banks which adopt the IFRS is 18.190% the predicted odds of failure of banks that did not adopt the IFRS, which may be ascribed to the increasing discretion in financial reporting permitted under these standards.

In Panel D of Table 5 we augment the baseline with the variable LISTED, which identifies whether or not the bank is listed in the stock market. The data were sourced from Bankscope. The descriptive statistics in Table 2 again point towards a higher failure rate of listed banks compared to non-listed banks: 0.516 for failed banks and 0.258 for non-failed banks; this is confirmed by the positive and statistically significant (1% level) relationship between LISTED and failure in the regression analysis. The predicted odds of failure of listed banks are 9.326% that of the failure of non-listed banks, which indicates the lower ability of capital markets to monitor banks.

In Table 6, Panel A, we augment the baseline with the variable which identifies the involvement of government in the economy (GOV_ROLE), identified in the Basel Accords as a mechanism to increase the soundness of banking systems. The data were sourced from the Economic Freedom Index. Larger values that attain a maximum of 66.300 indicate more government intervention, and lower values that attain a minimum of 0.000 indicate less government intervention in the economy. The descriptive statistics for GOV_ROLE in Table

2 averaged 34.049 (34.504 in countries with failed banks and 34.029 in countries without failed banks). Ireland is the country with the highest values (above 60 in the considered period) and Denmark and Sweden (which had no failed banks) the countries with the lowest values (below 10). The descriptive statistics point towards a higher failure rate of banks in countries where governments intervene more intensely, which is confirmed by the positive and statistically significant (1% level) relationship between GOV_ROLE and failure in the regression analysis. For every 1-unit increase in GOV_ROLE, the predicted odds of failure increase by 8.4%.

In Panels B and C of Table 6, we augment the baseline with two variables, CREDITOR_RIGHTS and SHAREHOLDER_RIGHTS, which identify whether the rights creditors and shareholders can exercise influence failure. The data were sourced from Brockman and Unlu (2009). Countries with low CREDITOR_RIGHTS get a score of 0 and countries with high CREDITOR_RIGHTS get a score of 4. Countries with low SHAREHOLDER_RIGHTS get a score of 2 and countries with high SHAREHOLDER_RIGHTS get a score of 5. The descriptive statistics in Table 2 point towards higher failure rates of banks in countries with both higher creditor rights: average of 1.941 with 2.091 in countries with failed banks and 1.941 in countries without failed banks, and also lower shareholder rights: average of 3.176 with 3.000 in countries with failed banks and 3.176 in countries without failed banks. The relationships of these variables in the regression analyses are however not significant at a statistically meaningful level.

In Table 7, Panel A, we augment the baseline with the variable BOARD_SIZE, which measures the size of the board. The variable is sourced from Bankscope and the descriptive statistics in Table 2 point towards a higher failure rate in banks with large boards: average of 18.392 board members, with 37.188 in failed banks and 15.119 in non-failed banks; this is confirmed by a positive and statistically significant (1% level) relationship between BOARD_SIZE and failure in the regression analysis. For every 1-unit increase in the BOARD_SIZE, the predicted odds of failure increase by 1%. In Panel B, we augment the baseline with the variable BOARD_TYPE, which indicates whether a bank adopts a two-tier board or not. The variable is sourced from Bankscope and the descriptive statistics in Table 2 point towards a higher failure rate in banks with two-tier boards: the average is 0.245, with 0.271 in failed banks and 0.240 in non-failed banks, i.e. most banks adopt a one-tier structure; this is confirmed by a positive and statistically significant (1% level) relationship between BOARD_TYPE and failure in the regression analysis. The predicted odds of failure of banks with two-tier boards is 4.187% the predicted odds of failure of banks with one-tier or other types of board. Both BOARD_SIZE and BOARD_TYPE point towards the inability of large and more complex board structures to appropriately monitor the activity of banks.

In Table 7, In Table B, we augment the baseline with the variable INDEP, which classifies the degree of independence of managers from their shareholders.[3] Based on data from Bankscope, the dummy INDEP assumes the value of 1 for the most independent banks (classified with "A"), and 0 otherwise. A higher degree of independence is indicative of complex management structures, which are related with a higher need of monitoring, and higher levels of default probability. The descriptive statistics for INDEP in Table 2 averaged 0.108, with a higher failure rate for more independent banks compared to less independent banks: 0.236 for failed banks and 0.085 for non-failed banks. This is confirmed by the positive and statistically significant (1% level) relationship between INDEP and failure in the regression analysis. The predicted odds of failure of more independent banks are 56.952% the predicted odds of failure of less independent banks.

Finally, in Table 8, we report further results on robustness tests. In Panel A, we augment the baseline with the variable SIZE, which measures the natural logarithm of banks' total assets. The data were sourced from Bankscope. The descriptive statistics in Table 2 point towards a higher failure rate of bigger banks: 18.365 for failed banks and 15.580 for non-failed banks; this is confirmed by the positive and statistically significant (1% level) relationship between SIZE and failure in the regression analysis. In Panel B, we augment the baseline with the variable RESTRICT, which identifies the level of restriction imposed on banks to undertake non-traditional activities. The variable is sourced from Barth *et al.* (2006). Larger values indicate a more restrictive environment to undertake non-traditional activities. The descriptive statistics in Table 2, average of 7.357, with 7.200 in countries with failed banks and 7.357 without failed banks, again point towards a higher failure rate of banks in countries with fewer restrictions; this is confirmed by the negative and statistically significant (1% level) relationship between RESTRICT and failure in the regression analysis. For every 1-unit increase in RESTRICT, the predicted odds of failure reduce by 61.1%. In Panel C, we augment the baseline with the variable TCR, the total capital ratio, again sourced from Bankscope. The descriptive statistics for TCR in Table 2 averaged 13.411

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[3] The indicator has five possible levels: "A" if shareholders have less than 25% of the direct or total ownership; "B" if one or more shareholders has an ownership percentage between 25% and 50%; "C" if one shareholder has more than 50% of the total ownership; "D" if one shareholder has more than 50% of the direct ownership; and "U" if the degree of independence from the shareholders is unknown.

(12.077 in countries with failed banks and 13.698 in countries without failed banks). The robustness test on TCR shows nonsignifcant results, which may point towards the ineffectiveness of this regulatory oversight measure in limiting failure.

6 SUMMARY AND CONCLUSIONS

Far less attention has been devoted to bank failures in the accounting finance literatures than to economic (bankruptcy) and financial (default) failure of corporations, which have a long tradition. With the exception of a few isolated cases of failures, such as the BCCI and Baring Brothers, or the Hestatt Bank that led to the institution of the Basel Capital Accords, there is currently little knowledge on the empirical factors that drove the failure of banks in the European Union.

Bank failures have remained an issue of serious concern to monetary and political authorities since the onset of the 2008 global financial crisis and more particularly the failure of Lehman Brothers. Monetary authorities are concerned about the functioning of monetary and financial markets and the consequent effect of supply of credit for the economy, and political authorities are concerned with mounting public pressure mainly fuelled by the cost of bailouts for taxpayers.

We collected data on 444 commercial banks from 19 E.U countries over the period from 2005 to 2010 to analyse bank failure, bailout of banks with public finances, in the wake of the 2008 financial crisis. Our findings indicate that financial accounting and macroeconomic variables critically determine the failure events. The loan loss reserves created by banks, the level of capital and performance critically determined the failure of European banks. Macroeconomic information, in particular the GDP, and public debt, augment the predictive ability of the models estimated with only financial accounting information. In addition to financial ratios and macroeconomic indicators rooted in the Basel Capital Accords and used in bank regulation and supervision, we find that several other indicators influenced failure in European banks. The following critically influenced failure: pertaining to the Eurozone, adopting international financial reporting standards, being listed, operating in countries that impose restrictions on banking activity, board size and type, bank's size and independence from shareholders.

Our findings are consistent with the recent regulatory reforms of the Basel Capital Accords underway that predict higher levels of capital and lower levels of risk for banks with the latter eventually leading to the separation of the commercial and investment banking activities, and with the view that macroeconomic conditions precipitated the financial crisis.

Our study contributes to the understating of the causes and consequences of the recent financial crisis with regards bank failure. Monetary authorities around the world can use the predictors from our model in the supervision of banks and the failure probabilities to assess pressure in the banking sector. Peer banks can additionally use the probabilities for pricing loans and their derivatives.

Our findings indicate that bank regulators and supervisors may find information besides financial ratios and macroeconomic indicators useful for monitoring commercial banks. Expanding the scope of regulation and supervision in the Basel Capital Accords could ultimately contribute to the soundness of the financial system.

Further understating of the causes and consequences of bank failure can be understood by expanding the scope of our model to predict bank failure with non-financial information. Information on executive compensation coupled with the distinct supervisory and regulatory regimes may unveil insights hitherto overwhelmingly promoted by the media. We leave the study of these issues for future research.

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8 APPENDICES

Table 1. Synopsis of bank failures in Europe. Statistics about the number of banks considered in the analysis and the number of banks with registered failure events. Data is reported by country of origin and by year. N = Number of banks considerer in the analysis; FAIL = Number of banks with failure events.

Country	N	2005	2006	2007	2008	2009	2010	FAIL
Austria	7	0	0	0	1	1	0	2
Belgium	5	0	0	0	3	0	0	3
Czech Republic	17	1	0	0	0	1	0	2
Denmark	27	0	0	0	0	0	0	0
Finland	4	0	0	0	0	0	0	0
France	71	0	0	0	9	1	0	10
Germany	10	0	1	0	1	0	0	2
Greece	14	0	0	0	1	5	2	8
Hungary	8	0	0	0	0	1	0	1
Ireland	12	0	0	0	4	0	0	4
Italy	99	0	0	0	0	3	0	3
Luxembourg	8	0	0	0	1	0	0	1
Netherlands	14	0	0	0	5	0	2	7
Poland	24	0	0	0	0	0	0	0
Portugal	16	0	0	0	2	1	2	5
Slovakia	13	0	0	0	0	0	0	0
Spain	27	0	0	0	0	0	0	0
Sweden	14	0	0	0	0	0	0	0
United Kingdom	54	0	0	0	4	0	1	5
FAIL	-	1	1	0	31	13	7	53
Observations	444	106	200	249	280	325	344	11.94%

Table 2. Data, sources and descriptive statistics. Description of the dependent and explanatory variables used in the analysis, their source, and summary statistics. FAIL and N-FAIL represents the average for failed banks and non-failed banks. T-test represents a two-sample mean comparison t-test.

Variable	Description	Source	N	Unit	Average	St. Dev.	FAIL	N-FAIL	T-test	Sig.
FAIL	1 if the bank was bailed out under the State Aid Program, failed, and 0 otherwise	European Commission	1,504	Binary	0.083	0.276	1.000	0.000	-	-
Financial ratios										
LLP_NIR	Loan loss provisions to net interest revenue	Bankscope	1,504	%	23.297	52.897	27.380	22.586	-4.794	
LLR_IL	Loan loss reserves to impaired loans	Bankscope	1,504	%	98.542	103.516	81.138	101.571	20.433	***
EQ_TA	Equity to total assets	Bankscope	1,504	%	7.996	6.394	5.221	8.479	3.258	***
ZSCORE	Z-score ((ROAA+EQ_TA)/σ(ROAA))	Authors calculation	1,504	%	47.946	434.235	15.675	53.564	37.890	***
ROAA	Return on average assets	Bankscope	1,504	%	0.605	1.231	0.406	0.640	0.234	**
CIR	Cost to income	Bankscope	1,504	%	64.678	33.310	66.459	64.368	-2.091	
IBR	Interbank loans	Bankscope	1,504	%	130.561	167.801	78.787	139.574	60.787	***
NL_TA	Net loans to total assets	Bankscope	1,504	%	61.154	21.445	56.425	61.977	5.552	***
Macroeconomic conditions										
GDP_GR	Annual growth rate of real GDP volume	Eurostat	108	%	1.751	3.595	1.110	2.285	1.452	
HICP	Harmonised consumer price indices.	Eurostat	108	%	2.417	1.528	2.500	2.348	0.106	
BUD_DEF	Budget deficit/surplus	Eurostat	108	Millions	-2.450	4.030	-3.726	-1.387	3.753	***
PUB_DEBT	Gross public debt	Eurostat	108	Millions	56.535	25.505	68.672	46.420	-6.995	***
PCREDITF	Private credit flow	Eurostat	108	Millions	12.437	18.679	14.226	10.947	0.242	
Qualitative information										
CDINFO	Depth of information índex	The World Bank	108	Multinomial	4.509	1.187	4.200	4.767	-3.211	***
Other Qualitative Controls										
EURO	1 if the bank is headquartered in the eurozone, and 0 otherwise	European Commission	110	Binary	0.636	0.483	0.809	0.633	-4.023	***
IFRS	1 if the bank adopts international financial reporting standards, and 0 otherwise	Bankscope	1,504	Binary	0.785	0.411	0.978	0.751	-14.482	***
LISTED	1 if the bank is listed on the stock market, and 0 otherwise	Bankscope	1,504	Binary	0.297	0.457	0.516	0.258	-7.207	***
GOV_ROLE	Role of government in the economy, measured by the level of government expenditures as a percentage of GDP. Minimum = 0; Maximum = 66.	Economic Freedom Index	110	Multinomial	34.049	15.863	34.504	34.029	-0.962	

Table 2. (continued)

CREDITOR_RIGHTS	Measures strenght of creditor rights. Minimum = 0; Maximum = 4.	Brockman and Unlu (2009)	17	Multinomial	1.941	1.088	2.091	1.941	-0.854	
SHAREHOLDER_ RIGHTS	Measures the strength of control rights granted by law to the minority shareholders: Minimum = 2; Maximum =5.	Brockman and Unlu (2009)	17	Multinomial	3.176	0.967	3.000	3.176	1.003	
BOARD_SIZE	Number of board members	Bankscope	1,504	Number	18.392	51.196	37.188	15.119	-2.762	***
BOARD_TYPE	1 if the bank has a two-tier structure and 0 otherwise	Bankscope	1,312	Binary	0.245	0.431	0.271	0.240	-0.928	
INDEP	Bankscope independence indicator, 1 if no shareholder has more than 25% of the direct or total ownership, and 0 otherwise	Bankscope	1,383	Binary	0.108	0.310	0.236	0.085	-4.918	***
SIZE	Natural logarithm of banks' total assets	Bankscope	1,504	Multinomial	15.993	2.212	18.365	15.580	-21.462	***
RESTRICT	Restrictions to undertake non-traditional activities. Minimum = 5; Maximum = 10.	Barth et al. (2004)	14	Multinomial	7.357	1.737	7.200	7.357	0.696	
TCR	Total Capital Ratio	Bankscope	1,125	%	13.411	8.196	12.077	13.698	4.846	***

Table 3. Correlation matrix, for financial ratios, macroeconomic conditions and qualitative information. Correlations at the 1% level of significance are in bold.

	FAIL	LLP_NIR	LLR_IL	EQ_TA	ZSCORE	ROAA	CIR	IBR	NL_TA	GDP_GR	HICP	BUD_ DEF	PUB_ DEBT	PCREDI TF
FAIL	1.000													
LLP_NIR	**0.097**	1.000												
LLR_IL	**-0.075**	-0.052	1.000											
EQ_TA	**-0.155**	0.032	0.062	1.000										
ZSCORE	-0.022	-0.020	0.003	0.002	1.000									
ROAA	**-0.146**	**-0.576**	**0.124**	**0.194**	0.017	1.000								
CIR	**0.076**	**0.217**	-0.054	0.045	-0.018	**-0.396**	1.000							
IBR	**-0.104**	**-0.085**	**-0.067**	**0.151**	-0.009	**0.083**	0.028	1.000						
NL_TA	-0.063	0.052	-0.006	**0.087**	-0.001	0.020	**-0.160**	**-0.163**	1.000					
GDP_GR	**-0.121**	**-0.287**	**0.149**	-0.015	0.012	**0.316**	-0.052	-0.019	-0.065	1.000				
HICP	**-0.086**	**-0.093**	0.016	0.007	0.000	**0.124**	-0.003	-0.015	0.028	**0.400**	1.000			
BUD_DEF	**-0.128**	**-0.248**	**0.265**	**-0.075**	-0.003	**0.213**	-0.005	-0.018	-0.007	**0.519**	**0.238**	1.000		
PUB_DEBT	0.063	0.050	**-0.230**	0.109	0.053	**-0.105**	0.043	0.047	**0.194**	**-0.404**	**-0.171**	**-0.407**	1.000	
PCREDITF	-0.010	**-0.104**	**0.232**	-0.015	-0.001	**0.120**	-0.009	-0.022	0.032	**0.460**	**0.267**	**0.447**	**-0.254**	1.000
CDINFO	-0.039	0.059	-0.029	0.016	0.035	-0.052	-0.058	-0.023	0.004	**-0.122**	-0.006	**-0.212**	**0.206**	**-0.082**

Table 3. (continued)

	FAIL	LLP_NIR	LLR_IL	EQ_TA	ZSCORE	ROAA	CIR	IBR	NL_TA	GDP_GR	HICP	BUD_ DEF	PUB_ DEBT	PCRE DITF	CDINFO
EURO	**0.152**	-0.007	-0.036	**-0.129**	0.031	**-0.103**	0.066	-0.017	**0.107**	**-0.192**	**-0.247**	-0.028	**0.531**	-0.007	**-0.138**
IFRS	**0.129**	0.031	**-0.109**	**-0.221**	0.024	-0.031	-0.002	**-0.113**	**-0.077**	0.052	**0.136**	-0.046	**0.151**	0.046	**0.142**
LISTED	**0.110**	-0.021	**0.135**	**-0.077**	0.049	**0.125**	-0.060	**-0.076**	-0.012	**0.167**	0.063	**0.085**	-0.063	**0.083**	-0.061
GOV_ROLE	0.038	**0.107**	0.042	0.025	-0.003	-0.049	-0.062	-0.041	-0.061	**0.175**	**0.217**	**-0.189**	**-0.233**	**0.170**	**0.229**
CREDITOR_ RIGHTS	-0.046	0.047	**0.082**	0.014	-0.002	**-0.081**	-0.023	-0.010	**-0.181**	-0.027	0.056	0.031	**-0.170**	0.010	**0.730**
SHARE HOLDER_ RIGHTS	**-0.088**	**0.070**	**0.252**	0.040	-0.018	**-0.082**	**-0.073**	0.028	**-0.073**	-0.057	-0.017	**0.077**	**-0.444**	**0.248**	**0.445**
BOARD_ SIZE	0.061	0.013	-0.019	-0.007	-0.014	**0.120**	-0.034	-0.034	-0.004	0.015	**0.203**	-0.064	-0.003	0.050	**0.071**
BOARD_ TYPE	0.027	-0.047	**-0.076**	**-0.073**	-0.025	**0.127**	0.043	-0.032	**-0.156**	**0.204**	**0.117**	0.057	**-0.217**	**-0.083**	**-0.157**
INDEP	**0.121**	-0.031	**0.208**	-0.043	**0.107**	0.064	-0.062	**-0.101**	-0.027	0.011	-0.016	**0.173**	**-0.071**	**0.078**	-0.050
SIZE	**0.353**	0.036	**-0.113**	**-0.463**	0.039	-0.060	-0.057	**-0.158**	**-0.229**	-0.012	-0.013	0.030	-0.027	0.036	**0.147**
RESTRICT	-0.057	0.007	-0.057	0.068	0.062	0.031	-0.013	0.053	**0.316**	**-0.133**	0.019	0.054	**0.643**	0.066	**-0.260**
TCR	-0.039	0.077	0.001	**0.590**	-0.007	0.040	**0.279**	**0.080**	**-0.258**	-0.022	0.009	0.008	**-0.098**	-0.023	0.023

Table 3. (continued)

	EURO	IFRS	LISTED	GOV_ROLE	CREDITOR_ RIGHTS	SHREHOLDER_ RIGHTS	BOARD_ SIZE	BOARD_ TYPE	INDEP	SIZE	RESTRICT	TCR
EURO	1.000											
IFRS	**0.098**	1.000										
LISTED	-0.012	**0.206**	1.000									
GOV_ROLE	**-0.091**	**0.382**	**0.171**	1.000								
CREDITOR_ RIGHTS	**-0.455**	**0.218**	-0.024	**0.440**	1.000							
SHREHOLDER_ RIGHTS	**-0.292**	**-0.072**	-0.052	**0.422**	**0.587**	1.000						
BOARD_SIZE	**-0.106**	**0.121**	**0.176**	0.022	-0.007	**-0.097**	1.000					
BOARD_TYPE	**-0.080**	**0.122**	**0.220**	-0.042	**-0.118**	**-0.469**	**0.184**	1.000				
INDEP	-0.045	0.053	**0.416**	**-0.078**	0.046	**0.114**	**0.231**	-0.041	1.000			
SIZE	**0.109**	**0.463**	**0.254**	**0.118**	**0.144**	**0.084**	**0.131**	**0.088**	**0.220**	1.000		
RESTRICT	**0.351**	**0.298**	**0.100**	-0.052	**-0.212**	**-0.429**	-0.070	**-0.326**	**0.091**	-0.168	1.000	
TCR	**-0.082**	**-0.107**	**-0.121**	0.052	**0.111**	**0.093**	-0.019	0.021	-0.006	-0.257	-0.089	1.000

Table 4. Panel A: Baseline model of failure of banks in Europe. Logit regression. Variables defined in Table 2. *** significant at the 1% level; ** significant at the 5% level; * significant at the 1% level.

Dependent: FAIL	Expected	Coef.	Odds Std. Dev.	Sig.
LLP_NIR	?	-0.005	0.995	
			0.005	
LLR_IL	-	-0.011	0.989	**
			0.005	
EQ_TA	-	-0.171	0.843	**
			0.073	
ZSCORE	-	-0.038	0.963	
			0.024	
ROAA	-	-0.412	0.663	*
			0.162	
CIR	+	0.012	1.012	
			0.008	
IBR	-	-0.007	0.993	**
			0.003	
NL_TA	+	0.011	1.011	
			0.017	
GDP_GR	-	-0.304	0.738	***
			0.072	
HICP	+	0.196	1.216	
			0.212	
BUD_DEF	?	-0.213	0.808	**
			0.071	
PUB_DEBT	?	0.012	1.012	
			0.014	
PCREDITF	?	0.033	1.034	**
			0.017	
CDINFO	-	-0.438	0.646	
			0.245	
Log-likelihood		-265.384		
Wald chi^2		44.970		
Prob > chi^2		0.000		
Nr. of observations		1,504		
Nr. of banks		444		

Table 4. Panel B: Predictive ability test of the baseline model. Deciles analysis.

Deciles	Baseline
1	36.800%
2	17.600%
3	9.600%
4	12.000%
5	9.600%
6	8.800%
7	3.200%
8	1.600%
9	0.000%
10	0.800%

Table 4. Panel C: Error classification analysis.

Cut-off	Type I	Type II	Correct
0.50	7.970%	45.450%	91.760%
0.06	2.350%	84.730%	59.640%
0.05	1.790%	85.590%	54.920%
0.04	1.570%	86.740%	49.340%

Table 5. Robustness tests for the baseline. Panel A: Financial ratios; Panel B: EURO; Panel C: IFRS; and Panel D: Listed. Variables defined in Table 2. *** significant at the 1% level; ** significant at the 5% level; * significant at the 1% level.

Dependent: FAIL	Expected	Panel A			Panel B			Panel C			Panel D		
		Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.
LLP_NIR	?	0.005	1.005		-0.004	0.996		-0.005	0.995		-0.004	0.996	
			0.006			0.005			0.005			0.005	
LLR_IL	-	-0.013	0.987	***	-0.010	0.990	**	-0.010	0.990	**	-0.011	0.989	**
			0.005			0.005			0.005			0.005	
EQ_TA	-	-0.139	0.870	*	-0.137	0.872	*	-0.144	0.866	*	-0.177	0.838	**
			0.063			0.069			0.071			0.074	
ZSCORE	-	-0.026	0.974		-0.040	0.961	*	-0.038	0.963		-0.034	0.966	
			0.020			0.021			0.024			0.022	
ROAA	-	-0.537	0.585	**	-0.396	0.673	*	-0.434	0.648	*	-0.425	0.654	*
			0.158			0.159			0.164			0.161	
CIR	+	0.010	1.010		0.010	1.010		0.012	1.012		0.011	1.012	
			0.007			0.007			0.008			0.007	
IBR	-	-0.007	0.993	**	-0.006	0.994	**	-0.006	0.994	**	-0.006	0.994	**
			0.003			0.003			0.003			0.003	
NL_TA	+	0.018	1.018		0.008	1.008		0.016	1.016		0.010	1.010	
			0.017			0.016			0.018			0.017	
GDP_GR	-				-0.324	0.723	***	-0.297	0.743	***	-0.319	0.727	***
						0.072			0.073			0.071	
HICP	+				0.320	1.377	*	0.180	1.197		0.202	1.224	
						0.248			0.208			0.211	
BUD_DEF	?				-0.247	0.781	***	-0.215	0.807	**	-0.199	0.820	**
						0.069			0.070			0.071	
PUB_DEBT	?				-0.010	0.990		0.007	1.007		0.011	1.011	
						0.015			0.014			0.014	

Table 5. (continued)

Dependent: FAIL	Expected	Panel A			Panel B			Panel C			Panel D		
		Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.
PCREDITF	?				0.030	1.031	*	0.030	1.030	**	0.032	1.032	*
						0.016			0.016			0.017	
CDINFO	-				-0.022	0.978		-0.552	0.576		-0.457	0.633	
						0.376			0.213			0.240	
EURO					2.948	19.062	***						
						20.937							
IFRS								2.901	18.190	*			
									27.849				
LISTED											2.233	9.326	***
												6.772	
Log-likelihood		-288.406			-262.465			-262.766			-261.658		
Wald chi^2		27.950			52.030			42.210			45.660		
Prob > chi^2		0.001			0.000			0.000			0.000		
Nr. of observations		1,504			1,504			1,504			1,504		
Nr. of banks		444			444			444			444		

Table 6. Robustness tests for the baseline. Panel A: Gov. Role; Panel B: Creditor rights; and Panel C: Shareholder rights. Variables defined in Table 2. *** significant at the 1% level; ** significant at the 5% level; * significant at the 1% level.

Dependent: FAIL	Expected	Panel A			Panel B			Panel C		
		Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.
LLP_NIR	?	-0.005	0.995		-0.001	0.999		-0.001	0.999	
			0.005			0.006			0.006	
LLR_IL	-	-0.010	0.990	*	-0.013	0.987	**	-0.012	0.988	**
			0.005			0.005			0.005	
EQ_TA	-	-0.181	0.834	**	-0.202	0.817	**	-0.203	0.816	**
			0.074			0.075			0.074	
ZSCORE	-	-0.034	0.966		-0.032	0.969		-0.028	0.972	
			0.026			0.022			0.021	
ROAA	-	-0.410	0.664		-0.343	0.710		-0.379	0.685	
			0.174			0.168			0.165	
CIR	+	0.013	1.013		0.011	1.011		0.010	1.010	
			0.008			0.007			0.007	
IBR	-	-0.007	0.993	**	-0.005	0.995		-0.004	0.996	
			0.003			0.003			0.003	
NL_TA	+	0.005	1.005		0.003	1.003		0.004	1.004	
			0.017			0.016			0.016	
GDP_GR	-	-0.343	0.709	***	-0.288	0.749	***	-0.331	0.718	***
			0.075			0.077			0.072	
HICP	+	0.150	1.162		0.015	1.015		-0.022	0.978	
			0.208			0.184			0.177	
BUD_DEF	?	-0.138	0.871		-0.149	0.862		-0.148	0.862	
			0.083			0.091			0.086	
PUB_DEBT	?	0.027	1.028	*	0.002	1.002		-0.018	0.982	
			0.016			0.016			0.017	
PCREDITF	?	0.032	1.032	**	0.072	1.075	**	0.072	1.075	**
			0.016			0.038			0.037	
CDINFO	-	-0.523	0.592		-0.476	0.621		0.159	1.173	
			0.218			0.463			0.619	
GOV_ROLE		0.081	1.084	***						
			0.034							
CREDITOR_ RIGHTS					0.082	1.085				
						0.479				
SHREHOLDER_ RIGHTS								-1.063	0.345	**
									0.176	
Log-likelihood		-260.756			-234.000			-232.069		
Wald chi^2		42.460			40.000			48.530		
Prob > chi^2		0.000			0.001			0.000		
Nr. of observations		1,504			1,430			1,430		
Nr. of banks		444			422			422		

Table 7. Robustness tests for the baseline. Panel A: Board size; Panel B: Board type; and Panel C: BvD Independence Indicator. Variables defined in Table 2. *** significant at the 1% level; ** significant at the 5% level; * significant at the 1% level.

		Panel A			Panel B			Panel C		
Dependent: FAIL	Expected	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.
LLP_NIR	?	-0.005	0.995		0.001	1.001		-0.003	0.997	
			0.005			0.008			0.006	
LLR_IL	-	-0.011	0.989	**	-0.009	0.991	*	-0.011	0.989	**
			0.005			0.005			0.005	
EQ_TA	-	-0.181	0.835	**	-0.235	0.791	**	-0.218	0.804	**
			0.073			0.085			0.074	
ZSCORE	-	-0.038	0.962		-0.035	0.966		-0.035	0.966	
			0.025			0.023			0.022	
ROAA	-	-0.442	0.643	*	-0.167	0.846		-0.347	0.707	
			0.162			0.332			0.224	
CIR	+	0.011	1.011		0.015	1.015		0.013	1.013	
			0.008			0.009			0.009	
IBR	-	-0.007	0.994	**	-0.006	0.994	**	-0.005	0.995	*
			0.003			0.003			0.003	
NL_TA	+	0.011	1.011		0.027	1.027		0.019	1.019	
			0.018			0.019			0.018	
GDP_GR	-	-0.294	0.745	***	-0.325	0.723	***	-0.301	0.740	***
			0.075			0.074			0.074	
HICP	+	0.149	1.160		0.189	1.209		0.195	1.215	
			0.203			0.221			0.220	
BUD_DEF	?	-0.202	0.817	**	-0.185	0.831	**	-0.218	0.804	**
			0.072			0.076			0.072	
PUB_DEBT	?	0.012	1.012		0.030	1.030	**	0.016	1.016	
			0.014			0.016			0.014	
PCREDITF	?	0.032	1.033	*	0.037	1.038	**	0.037	1.037	*
			0.017			0.018			0.020	
CDINFO	-	-0.450	0.638		-0.510	0.600		-0.450	0.638	
			0.248			0.241			0.263	
BOARD_SIZE		0.010	1.010							
			0.007							
BOARD_TYPE					1.432	4.187				
						3.803				
INDEP								4.042	56.952	***
									63.893	
Log-likelihood		-265.010			-239.068			-240.817		
Wald chi^2		38.570			48.250			52.760		
Prob > chi^2		0.001			0.000			0.000		
Nr. of observations		1,504			1,312			1,383		
Nr. of banks		444			372			401		

Table 8. Robustness tests for the baseline. Panel A: Bank size; Panel B: Bank restrict; and Panel C: Total Capital Ratio. Variables defined in Table 2. *** significant at the 1% level; ** significant at the 5% level; * significant at the 1% level.

Dependent: FAIL	Expected	Panel A			Panel B			Panel C		
		Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.	Coef.	Odds Std. Dev.	Sig.
LLP_NIR	?	-0.009	0.991		-0.003	0.997		-0.006	0.994	
			0.010			0.006			0.005	
LLR_IL	-	-0.014	0.986	*	-0.011	0.989	**	-0.013	0.987	**
			0.007			0.005			0.006	
EQ_TA	-	0.155	1.168		-0.234	0.792	**	-0.125	0.883	
			0.119			0.081			0.102	
ZSCORE	-	-0.057	0.944		-0.030	0.971		-0.047	0.954	*
			0.044			0.023			0.026	
ROAA	-	-1.434	0.238	**	-0.494	0.610	*	-0.404	0.668	
			0.164			0.160			0.178	
CIR	+	0.026	1.026	**	0.008	1.008		0.011	1.011	
			0.012			0.007			0.008	
IBR	-	-0.008	0.992		-0.014	0.986	***	-0.006	0.994	*
			0.005			0.005			0.004	
NL_TA	+	0.138	1.148	***	0.001	1.001		0.019	1.019	
			0.051			0.018			0.020	
GDP_GR	-	-0.200	0.819		-0.299	0.741	**	-0.285	0.752	***
			0.122			0.093			0.079	
HICP	+	0.160	1.174		0.055	1.056		0.148	1.160	
			0.323			0.219			0.219	
BUD_DEF	?	-0.449	0.638	***	-0.339	0.713	***	-0.272	0.762	***
			0.105			0.087			0.069	
PUB_DEBT	?	0.024	1.024		0.056	1.058	**	0.004	1.004	
			0.029			0.027			0.015	
PCREDITF	?	0.041	1.042	*	0.164	1.179	***	0.030	1.031	*
			0.024			0.052			0.016	
CDINFO	-	-1.973	0.139	***	-0.784	0.457	*	-0.753	0.471	*
			0.104			0.215			0.186	
SIZE	+	3.675	39.465	***						
			40.090							
RESTRICT					-0.944	0.389	***			
						0.132				
TCR	-							0.026	1.026	
									0.083	
Log-likelihood		-219.698			-228.675			-224.465		
Wald chi^2		23.550			43.530			41.130		
Prob > chi^2		0.073			0.000			0.000		
Nr. of observations		1,504			1,265			1,125		
Nr. of banks		444			374			336		