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European Banking Authority Stress Tests and Bank Failure: Evidence from Credit Risk and Macroeconomic Factors

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This study investigates the role of credit risk factors in predicting European bank failures in light of the recent financial (banking) crisis. Using data from 90 European Union (EU) banks in 21 countries (including 9 banks that failed the 2011 stress tests undertaken by the European Banking Authority), we employ a random effects probit model to analyze the relative impact of credit risk determinants and macroeconomic factors in predicting bank failure. The empirical analysis provides new insights that support the impact of credit risk and macroeconomic factors in the prediction of bank failure. Given that systematic risk associated with the banking system can impact both financial and real sectors, this empirical work offers insights for fundamental-based monitoring of banking institutions.

JEL classification: G21; G32; C33; C34
Keywords: Credit Risk; Bank Failures; Market Fundamentals; Random Effects Probit; European Banks

1. Introduction

It is well accepted in the literature that a healthy banking system is vital for economic growth and that a banking crisis can have negative repercussions for the real economy (Levine, 2005; Campello et al., 2010; Serwa, 2010). The recent financial (banking) crisis has demonstrated the need for further analysis of the factors contributing to bank failures and their role in triggering and propagating such crises. In other words, the banking system needs indicators that can serve as warning systems to identify potential bank failures in an efficient and accurate manner. The losses that banking institutions experienced in the recent crisis highlight the importance of such a warning system as regulators were forced to investigate a large number of banks and other financial institutions, mainly in the U.S. and Europe (Ivashina and Scharsfstein, 2009).

According to insolvency theory, a bank fails when the value of its assets declines below the value of its liabilities. The reason often attributed to the decline in the assets' value is the increase in credit risk due to the non-performance of loans. Moreover, as discussed by Brossard et al. (2006), an early warning system is a necessity for the detection of potential banking liquidity problems through the use of financial statement indicators alongside an assessment of the macroeconomic environment. Furthermore, the use of the off-site analysis by the International Monetary Fund to supervise current financial positions and to predict developing financial crises confirms the need to evaluate credit risk determinants associated with bank failures (Jagtiani et al., 2002).

Poghosyan and Čihak (2011) provide the only empirical study of the role of credit risks that contributed to bank failures in Europe. Their results indicate that asset quality, leverage, and earnings profile are the most substantial determinants of bank failures. Our study attempts to extend this line of inquiry by investigating the role of credit risk and macroeconomic factors in predicting European bank failures, especially in the aftermath of the recent financial (banking) crisis. Unlike Poghosyan and Čihak (2011) we include an extended array of financial indicators along with macroeconomic variables to enhance the explanatory power of our model. The analysis examines 90 banks in the European Union that participated in the 2011 stress tests conducted by the European Banking Authority (EBA) including the 9 banks that failed the stress tests and the remaining 81 banks which passed. In addition to in-sample predictions, our study also provides out-of-sample forecasting accuracy.

Section 2 surveys the recent literature on bank failures, while Section 3 presents the methodology and data employed. Section 4 reports the empirical results and Section 5 provides concluding remarks.

2. Recent Literature

The current literature on bank failures has emphasized the role of international and national macroeconomic variables along with a set of bank-specific factors in the formation of bank credit risk (Ariff and Marisetty, 2001; Cebenoyan and Strahan, 2004; Kraft and Jankov, 2005). At the same time, the majority of studies are related to developed markets (Fisher et al., 2000; Kraft and Jankov, 2005) and more precisely for the U.S. market (Ariff and Marisetty, 2001).

Pantalone and Platt (1987) identify the factors that contribute to U.S. bank failures following the deregulation actions in the 1980s. They use measures of management efficiency, profitability, leverage, risk diversification, and economic conditions as potential determinants of bank failures. Their empirical analysis shows that the factors underlying bank failures remained the same prior to and after the deregulation era. Thomson (1991) finds that the economic environment in which banks operate is a crucial factor in predicting bank failures. Berger and DeYoung (1997) show that the ratio of equity capital to total assets is the primary determinant of credit risk for banks, validating the moral hazard hypothesis, which implies that thinly capitalized banks tend to increase the lending of more risky loans, and thus to higher volumes of non-performing loans. Ahmed et al. (1998) find that loan loss provisions as a percent of total assets have a substantial impact on the size of credit risk as well as the deterioration in loan quality. Estrella et al. (2000) examine the effectiveness of alternative capital ratios in predicting bank failures. They provide empirical support for both the leverage and revenue ratios as predictors of bank failures. Takayasu and Yosie (2000) identify non-performing loans as the primary factor of credit risk, especially after the 1997 Asian financial crisis.

Salas and Saurina (2002) use panel data for Spanish commercial and saving banks to show that both macroeconomic and bank-specific factors affect non-performing loans and, consequently, bank failures. Hu et al. (2004) find an inverse relationship between bank size and nonperforming loans. At the same time, banks with higher government ownership display lower ratios for non-performing loans. Konstandina (2006) employs a multivariate panel logit hazard model to find a substantial role for both micro and macro factors in explaining bank failures for Russian banks. Thiagarajan et al. (2011) show non-performing assets play a significant role in a bank's credit risk profile in the case of India. Samad (2011) examines both failed and non-failed banks through ANOVA and Kruskal-Wallis tests to reveal that failed banks have lower capital ratios than their counterparts in non-failed banks. Samad and Glenn (2012) investigate the determinants of U.S. bank failures to show that Tier 1 risk-based capital to total assets, total risk based capital to risk weighted assets, returns on assets, total assets as percentage of full-time employees, and non-interest expenses have a significant influence in predicting bank failures. Finally, Ogut et al. (2012) attempt to forecast bank ratings by utilizing financial indices to determine those indices which serve a primary role in predicting bank failures for Turkish banks. Their findings indicate that the higher a bank's asset portfolio spent on government debt securities, the lower the probability of failure.

Another strand of the literature emphasizes the role of external factors, especially in the face of economic downturns, in forming expectations about bank failures. Financial crises are often related to the boom and bust cycles arising from the macroeconomic environment which tend to increase non-performing loans, and a higher proportion of bank failures. In particular, Ahmad (2003) and Kraft and Jankov (2005) argue that during the course of an economic downturn, the quality of assets deteriorates, leading to higher levels of credit risk and to higher capital requirements, which are proven to be highly costly and unobtainable. By contrast, Caprio and Klingebiel (1996) argue that rapid loan growth during economic booms is a primary factor for higher credit risk levels. In general, macroeconomic variables play a pivotal role in influencing bank failures by providing important information for effective policy making. For instance, the term structure of interest rates as well as GDP growth have been identified as two influential variables affecting the timing of bank survival, while variables associated with fiscal policy and the exchange rate regime have less significance in contributing to a higher probability of failures (Gonzalez-Hermosillo et al. 1996).

3. Methodology and Data

3.1. Methodology

We use a probit model in examining the impact of credit risk and macroeconomic factors in the prediction of European bank failures. To control for issues related to heteroscedasticity or non-normality, we utilize the robust estimation techniques proposed by Bertschek and Lechner (1998), a robust 'sandwich' estimator for the asymptotic covariance matrix of the quasi-maximum likelihood. The model is given in Equation (1) as follows:

$$y_i = x_i\beta + a_i + \varepsilon_i \tag{1}$$

where the latent dependent variable is a binary variable with 1.0 for failure to pass the stress test, and 0.0 otherwise, while it is assumed that the variance of ε_i is equal to 1 (Maddala, 1992; Bertschek and Lechner, 1998). a_i is an individual country-specific effect. Here the β vector of parameters is estimated by using the cluster corrected covariance matrix method of maximum likelihood and Newton's method from the following function:

$$log\ L(\beta) = \sum_{i=1}^{N} y_i\ logF(x_i'\beta) + \sum_{i=1}^{N} (1\text{-}y_i)\ log[1\text{-}\ F(x_i'\beta)] \tag{2}$$

where F(.) is the standard normal distribution function. We assume the a_i are either fixed or random. We need to assume random effects instead of fixed effects, as the fixed effects probit model lacks a consistent estimator of the vector β.

3.2. Data

We use the years 2010 and 2011 for 90 European banks across 21 countries that participated in the 2011 stress tests organized by the EBA. These 90 banks represented 65% of the assets in the European banking sector. Note that nine of the banks failed to pass the stress tests and include five banks in Spain (Caga Mediterraneo, Catalunya Caixa, Unmin, Caja Tres, Banco Pastor), two banks in Greece (Eurobank, ATE Bank), one bank in Austria (Volksbank) and one bank in Germany (Helaba Bank).[1]

Quarterly data for various credit risk ratios along with other banking and macroeconomic variables were obtained from *Bloomberg* and *Datastream* databases. Table 1 displays the variables along with the relevant data source. Asset quality is proxied by measures pertaining to loan performance ratios, such as non-performing loans to total loans (NPLL) and non-current loans to total loans (NCLL). It is hypothesized that both increases in non-performing loans to total loans and non-current loans to total loans each increases a bank's vulnerability and likelihood of failure.

Bank capitalization is measured as the ratio of capital to risk-weighted assets (T1). The Tier I ratio represents a capital buffer for loss absorption with increases in this ratio reducing the likelihood of bank failure. The capital adequacy ratio is important in establishing bank soundness as a part of the initiation of a Pan-European system of banking supervision - either independently or under the umbrella of the European Central Bank (De Larosiere, 2009). The leverage ratio (LEV), defined as total assets to total common equity (LEV), serves as an indicator associated with the pricing of default risk. The higher leverage ratio (lower capitalization) ratio, the greater the default risk.

[1] Note that Helaba Bank refutes its performance on the stress tests.

Managerial quality (MQ) is measured as the ratio of operating expenses to total revenues. A lower ratio signals management's ability to reduce expenses, thus a lower likelihood of bank failure (Kick and Koetter, 2007). The net interest income ratio (NII) is a measure of risk taking by a bank defined by the lending margin charged. Given that loans are priced in accordance with their risk margin, a higher lending margin implies higher risk taking, thus a greater probability of default. The return on assets (ROA) reflects a bank's profitability with a higher ratio reflecting greater prospects for growth, thereby reducing the likelihood of bank failure. With deposits considered a stable funding source for a bank, a higher loan to deposit ratio (LD) reflects a greater reliance on non-deposit funding sources which raises the bank's credit risk.

Table 1
Variable Definitions

NPLL	Non-performing loans/total loans, *Bloomberg*
NCLL	Non-current loans/loans, *Bloomberg*
T1	Tier I = capital divided risk-weighted assets, *Bloomberg*
LEV	Leverage ratio = total assets/total common equity, *Bloomberg*
MQ	Management quality = operating expenses/total revenues, *Bloomberg*
NII	Net interest income ratio, *Bloomberg*
ROA	Return on assets, *Bloomberg*
LD	Loans/deposits, *Bloomberg*
LATA	Liquid assets/total assets, *Bloomberg*
VEP	Market risk = the variance of bank's equity price, *Bloomberg*
DY	GDP growth, *Datastream*
CDS	Country's Credit Default Swaps Spread, *Bloomberg*
NPL	Banking sector's overall non-performing loans, *Datastream*
LIBOR	The LIBOR-OIS spread, *Bloomberg*

A bank's liquidity position is proxied by the ratio of liquid assets to total assets (LATA). This measure shows the degree to which banks can withstand a sudden liquidity crisis. The higher share of liquid assets would make the bank more resilient to liquidity pressures. Market risk is measured by the variance of a bank's equity price (VEP). Since this measure of volatility essentially assesses the uncertainty of the return on investment of the bank's equity, increases in such market risk are positively associated with the probability of bank failure. In addition to credit risk factors and given the fact that the crisis period is explicitly considered, we also include macroeconomic factors that are directly linked to systematic risk: GDP growth (DY), the country's credit default swap spread (CDS), based on a contract maturity of 5 years[2], the non-performing loan ratio of the country (NPL) and the LIBOR spread (where the LIBOR spread is the difference between the LIBOR interest rate and the overnight indexed swap rate, so that the spread represents the degree to which banks are willing to lend to each other).[3] A higher growth rate in GDP signals positive improvements in the economy which should reduce the likelihood of bank failure (Berg et al., 2004; Beck et al., 2006; Čihak and Schaeck, 2007), while higher CDS spreads, higher non-performing loans, and higher LIBOR spreads signal negative signs for the banking sector, implying a higher likelihood of bank failure.

[2] Spreads with this maturity are chosen since 5-year spreads are used the most for credit default swaps, and also because the common contractual maturity of CDS spreads lies between 1 and 10 years (Fontana and Scheicher, 2010).

[3] For U.S. banks Curry et al. (2003) suggest these factors play a significant role while for other countries the opposite is the case (Bongini et al., 2002).

4. Empirical Analysis[4]

4.1. In-Sample Estimation

Table 2 presents the base case, 'pooled estimator', which represents the simple probit estimator that treats the entire sample as if it were a large time series cross-section. The model exhibits overall predictive power with a pseudo-R^2 statistic of 41 percent. The results indicate that each independent variable is statistically significant while it carries the theoretically expected sign.

Table 2
Random Effects Probit
(In-Sample Estimation)

Variable	Coefficient
NPLL	0.513*
NCLL	0.272**
T1	-0.366*
LEV	0.295**
MQ	0.461*
NII	0.411*
ROA	-0.372*
LD	0.242**
LATA	-0.484*
VEP	0.379*
DY	-0.318**
CDS	0.271**
NPL	0.186***
LIBOR	0.238**
Pseudo-R^2	0.410
Log L	-762.900

Notes: logL is the maximum likelihood function estimation. Critical values at 1%, 5% and 10% are 3.21, 2.34, and 1.70, respectively. *, **, and *** denotes statistical significance at 1%, 5%, and 10%, respectively.

The financial ratios which proxy asset quality yield the anticipated coefficient signs as increases in non-performing loans to total loans (NPLL) and non-current loans to total loans (NCLL) each increases the likelihood of bank failure. With respect to bank capitalization, an increase in the ratio of capital to risk-weighted assets (T1) reduces the chance of bank failure. Furthermore, the greater the leverage ratio (LEV), the higher the default risk and bank failure.

An increase in the ratio of operating expenses to total revenues, as a measure of managerial quality (MQ), increases the likelihood of bank failure. The same is true for net interest income (NII) which measures bank risk taking defined by the lending margin. We find that an increase in a bank's profitability defined by the return on assets (ROA) reduces the likelihood of bank failure. We also find that a higher loan to deposit ratio (LD) increases the bank's credit risk and chance of failure. An increase in the ratio of liquid assets to total assets (LATA) reduces the likelihood of bank failure. In terms of market risk indicators, an increase in the variance of a bank's equity price (VEP) increases the likelihood of bank failure. In terms of the macroeconomic factors, an increase in GDP growth (DY) indicates an improving macroeconomic environment which reduces the chance of bank failure. Increases in a country's CDS spreads, in non-performing loans ratios for the entire banking sector,

[4] RATS version 8.0 software is used in the empirical analysis.

and in LIBOR spreads, lead to a more adverse environment for the banking institutions and, therefore, increases the likelihood of bank failure.

Finally, while we recognize that bank fragility may be caused by bank strategies that proved overly risky (captured by the bank-specific variables) or by adverse macroeconomic conditions (captured by the country-specific variables), there might be some feedback loops in operation. We could also test for such loops through interaction terms between the country's credit default swap spread (CDS) with some bank-specific variables, such as, CDS*NPLL, CDS*T1, CDS*NII, and CDS*ROA. According to Gennaioli et al. (2010), a loss of credibility in government debt almost inevitably has the effect of reducing investment and output growth, thereby reducing the tax base available to service the debt. This loop operates through the banking system, although it could also operate through other channels, such as reduced household wealth, confidence, and consumption, but these alternatives channels are out of the research scope of this study. The results with these feedback loops are reported in Table 3. These empirical findings document that although the interaction terms display the expected sign, they are all statistically insignificant.

Table 3
Random Effects Probit
(In Sample Estimation plus Feedback Loops)

Variable	Coefficient
NPLL	0.427*
NCLL	0.236**
T1	-0.308*
LEV	0.277**
MQ	0.439*
NII	0.424*
ROA	-0.361*
LD	0.225**
LATA	-0.451*
VEP	0.346*
DY	-0.305**
CDS	0.258**
NPL	0.162***
LIBOR	0.214**
CDS * NPLL	0.106
CDS * T1	-0.074
CDS * NII	-0.081
CDS * ROA	-0.119
Pseudo-R^2	0.470
Log L	-905.400

Notes: logL is the maximum likelihood function estimation. Critical values at 1%, 5% and 10% are 3.21, 2.34, and 1.70, respectively. *, **, and *** denotes statistical significance at 1%, 5%, and 10%, respectively.

4.2. Out-of-Sample Predictions

Table 4 reports the out-of-sample prediction accuracy for the probit model based on estimation at year 2010 (available upon request) which makes use of the same explanatory variables identified for the in-sample estimation. The available data for the 90 banks for the year 2010 and the corresponding coefficient estimates are used to forecast bank failures for 2011. Specifically, we sort all 90 banks from the out-of-sample period (2011) based on their predicted failure probability values obtained from the fitted coefficients from the in-sample estimation. These predicted failure probability values are classified into the five highest probability deciles in the year the stress tests were implemented. The first column of Table 4 presents the out-of-sample year, i.e. the year 2011. The second column displays the rankings of worst predicted probabilities. The third column lists the accumulated accuracy percentage. The results identified 74.28% of the 90 banks over the out-of-sample period (year 2011), while it classified 85.11% of the 90 banks in the highest failure probability decile. The model also does well in identifying banks from above the median predictive failure probability at 99.63%.

Table 4
Out-of-Sample (2011) Prediction Accuracy

Worst Predicted Probability (%)	Accumulated Predictive Accuracy (%)
5	74.28
10	85.11
20	90.73
30	96.82
40	97.69
50	99.63
50-100	100.00

Notes: The predictions are based on the random effects model.

Table 5
Model Accuracy for 2011 Out-of-Sample Predictions

	Pass the stress test	
Critical value	% Correct	% Incorrect
0.5	83.38	16.62
0.6	85.32	14.68
0.7	90.19	9.81
0.8	93.61	6.39

Table 6
Predicted Failure Probabilities for 2011

Bank	**Probability at 2011**
Caga Mediterraneo	0.6128
Catalunya Caixa	0.5034
Unmin	0.6347
Caja Tres	0.6977
Banco Pastor	0.5681
Eurobank	0.5046
ATE Bank	0.9176
Volksbank	0.4672
Helaba Bank	0.4674
Average	**0.6019**

The critical value for failure probability is set equal to 0.50. If the probability of failure calculated from the probit model is greater than this value, it is classified as a failure. Raising the critical value for the classification as a failure increases the type II error of failure, but reduces the extent of the type I error (i.e. incorrectly identifying a failing bank as a survivor). The results, based on the random effects model, are reported in Table 5 and indicate that the model is able to accurately predict bank failure for both surviving banks and all banks that failed to pass the stress test. The prediction estimates display a very high out-of-sample accuracy (over 80%), indicating that the financial and macroeconomic variables used in the probit model can successfully predict potential bank problems in the European banking industry.

Note that one change that could dramatically affect the forecasting accuracy of binary models is the selection of a critical value for failure. According to Barr and Siems (1999), a change in the critical value could significantly alter the number of Type I and Type II prediction errors. Table 5 also displays the robustness results following changes in the critical value. Overall predictive accuracy does not decrease even when the critical value is set to 0.8. The probit model can predict a relatively high number of failures.

Finally, we make use of our estimated results to provide explicit predictive probability failure results for the 9 European banks that actually failed to pass the stress tests conducted by the European Banking Authority. These exercise results are reported in Table 6. For instance, for the case of the Greek ATE bank, the probability of failure is as much as 91.76%.[5]

5. Concluding Remarks

This study provides an analysis of the role of credit risk and macroeconomic factors in the prediction of potential bank failures in light of the 2011 stress tests by the European Banking Authority. To this end, a sample of 90 European banks in 21 countries for year 2011 (including these nine banks that failed the 2011 stress tests by the EBA) was used in the estimation of a random effects probit model. The results indicated that both credit risk and macroeconomic factors are significant determinants of bank failures. In particular, the results suggested that more vulnerable European banking institutions show a greater likelihood of failure predicted by higher ratios of non-performing loans to total loans and non-current loans to loans. Also, lower capital adequacy ratios based on the Tier I capital, a higher leverage ratio, lower management quality, a lower net interest income ratio, lower returns on assets, a higher loans to deposits ratio, a lower ratio for liquid assets to total assets, greater variance of a bank's equity price, lower GDP growth, higher CDS spreads, higher overall banking non-performing loans ratio and a higher LIBOR spread each contribute to a greater likelihood of bank failure. Moreover, the model performs satisfactorily in terms of out-of-sample (2011) predictive accuracy.

By establishing a link between financial and market fundamentals for European banks and the probability of their failure, this empirical work offers insights for fundamental-based monitoring of banking institutions. Therefore, by documenting that the health of a banking institution is a function of its latest financial conditions along with the macroeconomic environment, we can provide empirical support to bank regulators' request to use an early warning system that will monitor the health of banking institutions. In other words, market regulators have access to additional warning signals that could produce forward looking failure risk assessments about the vulnerability of banking institutions. Regulatory authorities must evaluate the risk embedded in a bank's activities and, thus, understand the factors that impact failure risk. In addition, given the fact that the probability of bank failures also depends on intrinsic factors, bank managers can exploit this information to evaluate a bank's risk position and, therefore, to adjust their oversight policy accordingly. Therefore, our empirical findings can be used not only by bank regulators, but also by policy makers and for bank risk management. Further research work would benefit by comparing banking systems in terms of their bank failure predictability from different regions around the globe.

[5] The recent September 2012 merger of this problematic bank with a healthier bank validates our empirical results.

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