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The role of capital in bank failures across EU-15 countries: backward LR approach

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Abstract. Resolving the puzzle which financial indicators persistently indicate severe disruptions in the business of banking, is of the utmost importance for prudential authorities. Thus, the intent of this paper is to outline microeconomic determinants of bankruptcies within the banking sectors of the EU-15 countries and to clarify the role of bank capital in it. Namely, the bank capital regulation is designed as both, ex-ante (bankruptcy prevention) and ex-post (bankruptcy costs reducer) regulatory instrument. Backward stepwise logistic regression was applied on the Bankscope data sample of around 60 commercial banks in the period that preceded the global financial crisis. Estimations were obtained for the year in which a certain bank bankrupted as well as for each year over the five-year period prior to the bankruptcy. Research findings confirm that a number of financial indicators, such as asset quality and liquidity indicators could serve as early warning signals of bank failures even five years before the bankruptcy. The results for bank capital ratios were non-persistent regarding their sign and significance in the year preceding the bankruptcy and several years prior to bankruptcy. Finally, the most convincing results speak in favor of the too-big-to-fail phenomenon, as bank size explains the most of its survival odds.

Keywords: backward stepwise logistic regression, bank failures, capital regulation, commercial banks, EU-15

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1. Introduction

Bank bankruptcies are rather sparse events. For instance, only 1.75% of the US banks went bankrupt in 2009 [29, 8], the year of the worst financial crisis since the Great Depression, while many of them were bailed out and/or merged with the sound ones. A thorough regulation of the business of banking, as well as the existence of deposit insurance schemes, successfully prevent the occurrence of bank runs and significantly diminish liquidity issues. A possibly severe impact of bank failures on the overall banking sector stability is frequently avoided by the lender of last resort actions in case of the too-big-to-fail banks or nowadays systemically important banks, which are regularly paid with the public money. However, liquidations and failures obviously still take place in the banking market. Therefore, reaching conclusions about financial indicators, which might signal bank failures and bankruptcies, is an important theoretical and empirical issue, with a valuable practical implication recognized in reducing the chances of wasting public money through corrective actions as well as preventing the contagion from spreading throughout the financial system. In such a manner, previous as well as future examinations in this area should be praised.

Many scholars have attempted to reach some definitive conclusions on the determinants of bank bankruptcies, with the main goal of timely predictions of troublesome banks in the future. However, conclusions on financial ratios that signal bank failures effectively suffer from the problem of being descriptive rather than predictive. Furthermore, this phenomenon should be investigated in times when a large number of banks go bankrupt in order to have a sufficient number of observations and valid statistical results, rather than insisting on recent data [19]. The aforementioned means that examinations of bank failures are predominantly reserved for the periods of systemic banking crises. On the other hand, focusing on such a time span could be troublesome as bank failures in these circumstances could be driven more by the macroeconomic factors and not by the controllable aspects within the bank management. In a nutshell, a compromise between a perfect application of statistical methods, which requires a sufficiently large data sample and an economic sense of the analyzed problem is required. Thus, detecting bank vulnerabilities or predicting their distress are more frequently analyzed than the puzzle about the determinants of bank bankruptcy is being solved, especially in Europe where outright bank failures are quite rare [23, 4] in comparison to the US banking industry, which has a large number of operating (and consequently failing banks) due to its history of state banking restrictions.

This paper centers on microeconomic indicators of bank failures, which assumes a solid institutional and sound economic framework and, therefore, an absence of the systemic banking crisis. Namely, macroeconomic factors are critical for identifying systemic banking crises, while microeconomic factors play a more important role in describing individual bank failures. Lin and Yang [20] confirm the joint impact of bank fundamentals and economic conditions for bank failures in 11 East Asian markets for the 1999-2011 period, but still notice that bank fundamentals play a more critical role in predicting bank failures than the macroeconomic factors. Therefore, choosing the EU-15 area in the period that preceded the global financial crisis was a part of an empirical strategy. Financial indicators, which were presupposed to explain bank failures, were selected on the basis of the earlier body of knowledge on the determinants of bank failures as well as the highest data availability, following the main idea that indicators, which usually form the umbrella term CAMELS, should indicate bank failures. In addition, bank capital ratios are in the spotlight as the bank capital regulation was designed as both ex-ante and ex-post regulatory mechanism. Ex-ante should prevent bank shareholders and managers from the excessive risk-taking and thus decrease the likelihood of bank bankruptcy, while ex-post should lessen the public costs and increase the private costs of bank failures. However, more than 30 years after the bank capital requirements known as the Basel accords were announced, disputes concerning this regulatory regime (counter)productivity still occupy the scholars' attention and are a part of public discourse in the field of managing banking stability. The significance of the topic is altered with the new – Basel IV capital requirements regime on the horizon. Not many papers focused on the role of bank capital regulation in their failures, e.g. [11], [6], [7], [3], [22], [21], [1], [26] did, which increases the present study relevance.

In this study, a logistic regression was run on the data sample consisting of approximately 400 commercial EU-15 banks, as well as on the data for around 60 commercial banks when the subsampling approach was adopted. Namely, there was only up to 10% of bankrupt banks in the full sample, and the subsample approach was introduced in order to balance the number of active and failed commercial banks, which was inspired by Pervan et al. [27], Serrano-Cinca et al. [29], and Cleary and Hebb [8]. Many authors tested the predictive aspect of their models by looking back three years before a failure [21], two years before a failure [4], [22], but mostly a year before the bankruptcy. Our estimations were obtained for the year in which the bank bankrupted as well as for each year over the five-year period that preceded the bankruptcy, as seen in Cole and White [9] and Serrano-Cinca et al. [29], in order to get more detailed answers about the persistency of micro-financial indicators over the years for detecting bank failures. The obtained results mainly speak against the capital ratio capability of predicting bank failures persistently several years before the failure. Thus, there is no ground to blame a more restrictive capital regulation for bank failures. On the contrary, the results confirm that capital regulation is a solution rather than a threat to the banking sector's stability. Furthermore, its possible connection to bank failures is a symptom, rather than the cause of troubles in the business of banking.

The evidence provided in this article contributes to the literature within banking regulation/stability in a number of ways. Firstly, attention is given to bankrupt banks rather than distressed ones, which is often the case in empirical research on the banking industry. Secondly, this is a cross-country study as the EU-15 banks are at the center of the research since the evidence for this area is still scarce. Furthermore, in order to focus on bank-specific factors and minimize the remaining uncontrollable, external factors of bank bankruptcies, this research encompasses the period prior to the economic bust imposed by the global financial crisis. Namely, macroeconomic imbalances/disturbances and structural problems as the prevalent causes of bank distress were already examined by Männasoo and Mayes [23], who took into consideration 19 Eastern European economies over the 1995-2004 transition period, and Betz et al. [4] who investigated large EU banks from 2000-2013. Finally, the role of capital regulation in bank failures was examined, as the usual criticism of this regulatory concept largely incorporates the risk-taking argument while mostly neglects capital requirements and bank failure nexus. In the latter aspect, the paper idea corresponds to Männasoo and Mayes [23] and Abou-El-Sood [1].

The remainder of the paper is organized as follows. Section 2 conducts the survey of literature on the determinants of bank failures, emphasizing those that tackled the role of capital regulation. The third section discusses the methodology applied, the data, and the results of the empirical analysis, while section 4 concludes the paper.

2. Literature review

There is a disparity in drivers and definitions of troublesome banks within the bankruptcy literature in the banking business area. Hereinafter only articles that accentuated the role of bank capital in their instability/bankruptcy are summarized due to paper size restrictions and concerning the selected research problem. Reviewed literature is far from a complete survey on the capital regulation implications for the banks safety and soundness, as well as the empirical background regarding the determinants of bank failures. It should rather be considered as an illustration of key messages of quite modest research establishing the empirical linkage between capital regulation and bank failures.

The greatest of all difficulties when complying with the capital requirements regulation lies in the threat that higher capital requirements will increase credit price due to higher costs of financing. Consequently, either credit risk will build up or loans will become less affordable and available, i.e. a credit contraction occurs and slows down the economic growth. According to the moral hazard theory, it is more likely that banks will shift their assets towards riskier choices to sustain expected income [18], [17], [14], [28], [5], which enlarges the odds for bank failures. Thus, more restrictive capital requirements might cause bank failures. Contrary to that view, the capital buffer theory [24] apostrophizes a prudent behavior of bank managers and shareholders when investing a higher pledge against the risk they undertake. To be more precise, the so-called capital-at-risk effect [13], [16] is noticed and although higher capital requirements might increase the assets risk up to a certain point, after the optimum interest rate is reached, the credit-rationing phenomenon will follow, while at the same time the overall financial risk will be reduced. Thus, higher bank capital will not enlarge the chances for bank bankruptcy, but quite the opposite – downsize it.

On the other hand, an insignificant effect of the bank capital level in describing/predicting bank failures might be recorded in the case of the zero-sum effect between higher assets risk and lower financial risk. In addition, having more capital might be beneficial to banks for several practical reasons, other than survival, but consequently interacted with their survival chances. Some of them are [12]: 1) entering profitable opportunities during the economic downturn, which would be disabled in the case of capital shortages, 2) avoiding high compliance costs imposed by the capital requirements regulation (transaction costs, signaling costs, opportunity costs), 3) maintaining targeted credit rating and credit capacity of the bank, which directly influences financing availability and affordability, and finally 4) sustaining long-term operating flexibility and fulfilling other strategic goals. Finally, only solvent but temporarily illiquid banks can count on the lender of last resort assistance as capital is, up to a certain level, protection against unexpected losses imposed by shocks, which diminishes the credit risk exposure of the central bank.

In such a manner, Chiu et al. [7] concluded that higher capital adequacy lowered the risk and reduced the bankruptcy chances of 36 Taiwanese commercial banks in the 2002-2004 period, while Liu [21] confirmed that conclusion, with a difference of employing the Tier 1 capital ratio in a cross-country study on the factors of bank liquidity distress by using the data for 772 banks from the OECD, NAFTA, ASEAN, EU, NIC, G20, and G8 countries three years before the failure. On the other hand, Pereira Pedro et al. [26] did not verify either the importance of the solvency ratios or more restrictive regulation in predicting banking crises for nearly 3,000 publicly listed banks from 33 OECD countries in the 1991-2011 time span. According to them, regulatory and supervisory practices are irrelevant in bankruptcy prevention. Quite the opposite from the aforementioned surveys, Brana and Lahet [6] found that more restrictive capital requirements substantially increased the probability of financial crisis in Asia due to capital shortages, which led to fire sales of riskier assets, reduced cross-border lending and wholesale funds withdrawal, rather than fulfilling the role of crisis prevention in the banking sector. Furthermore, Berger and Bouwman [3] documented beneficial effects of the appropriate solvency level for bank survival during the crisis times. Moreover, for the small banks, it is a precondition of going concern and increasing market share at all times, regardless of the economic cycle phase. In contrast, for the medium and large banks, the capital level might be important primarily during banking crises as confirmed for the US banks between 1984 and 2010. According to Abou-El-Sood [1], bank regulatory capital ratios signaled bank failures appropriately for 560 US bank holding companies only when they were below 6% of the core capital ratio in the 2003-2009 period, and below 8% during the financial crisis period of 2007-2009. In other words, the well-capitalized banks were not brought into distress due to the capital requirements regulation, which later became a part of Basel III capital requirements, in the observed 2003 to 2009 time period. Thus, establishing an appropriate threshold that differentiates well-capitalized banks from the other ones is paramount for maintaining banking sector stability, as it might signal the troublesome banks timely, i.e. before their condition worsens due to economic downturn when collecting additional and adequate capital becomes a difficult task. Finally, according to Abou-El-Sood's [1] evidence, bank size and loan provisioning turned out to be more important predictors of bank distress.

Indeed, increasing capital quantity and quality (core capital) was a life-saving solution for US banks that did not go bankrupt in the global financial crisis, as their increased riskiness was pledged with sufficient regulatory capital [29]. According to Serrano-Cinca et al. [29], worsening of US banks' solvency position, lower profitability and insufficient income to cover overheads were only the symptoms of bank bankruptcies. The true origin of bank disasters were poor business diversification (for instance excessive concentration on the real estate loans) and rapid loan growth (close to 20% yearly), which increased bank riskiness and reduced stable/structural sources of bank profitability. Thus, bank capital should not be perceived as a cause of bank failures, but rather as a mirror of either success or failure in defining and implementing bank strategy. Similarly, DeYoung and Torna [10] claimed that nonperforming loans, cost inefficiency, equity and ROA are potentially endogenous to the financial condition of the banks. They also reported that bank capital is associated with a reduced probability of their failure in the US. Somewhat earlier, Cole and White [9] confirmed the importance of the loan portfolio composition for US bank failures (concentration on certain types of mortgages), and explanatory power of bank capital ratio for predicting failures up to two years prior to failure, while earlier than that it was usually insignificant. In addition, Jin et al. [15] confirmed that US banks that failed during the last financial crisis had a lower Tier 1 capital ratio. To sum up, maintaining a high quality/equity capital surely adds to bank stability, as confirmed again for US banks by Cleary and Hebb [8]. On the other hand, building regulatory capital via add-backs, e.g. by increasing loan loss reserves (up to a certain limit), raises the odds for bank bankruptcy and makes them less restrictive in lending when their loan quality is already deteriorating [25]. Thus, besides capital level, its structure also matters for the bank's performance and survival.

Finally, when compared to risk-weighted capital ratios, simple leverage/capital ratios might have higher explanatory power in predicting bank bankruptcies [11], [22], especially if the loan quality variables are used to measure credit risk, which is largely captured with the regulatory capital ratios [3]. Based on a quarterly data set of nearly 16,200 FDIC-insured US banks over the 1992-2012 time period, Mayes and Stremmel [22] reported that the non-risk-weighted capital measure explains bank distress and failures with considerable accuracy and becomes an especially important early warning signal in case of complex bank business models and environments. Thus, the leverage ratio slightly outperforms the risk-sensitive capital ratio in predicting bank distress and failures. Namely, a simple leverage ratio is more transparent, hard to manipulate or interpret discretionarily and it clearly demonstrates problems once they appear on the horizon, while more sophisticated capital adequacy indicators might be more useful in normal times.

Altogether, there is solid empirical evidence that higher capital level is beneficial for bank survival. However, according to the capital buffer theory, capital level and asset riskiness are mutually driven, and bank capital is usually increased ex-ante to support further bank growth and additional asset risk accumulation. Thus, the following hypothesis is established:

Hypothesis 1 (H1). *Higher bank capital increases the chances for bank survival in the year preceding the bankruptcy, but also increases the chances for bank bankruptcy several years prior to bankruptcy.*

3. Data, methodology and results

Data issues can be a tremendous obstacle for researching certain areas, but nothing compares to the challenges when investigating rare events such as bank bankruptcies. The problem is additionally worsened when dealing with the banking industry, as the indicators of possibly highest prediction accuracy are usually confidential supervisory data. This study analyzes individual banks dataset in the EU-15 area in the years that preceded the global financial crisis to obtain unbiased results (from the overall economic conditions) and reach general conclusions about bank fundamentals importance, particularly bank capital level, for predicting bank bankruptcies. Data availability, i.e. the trade-off between the number of observations and the number of financial indicators, were additional reasons for setting up such a data selection criterion. The data were taken from the earlier version of the BvD BankFocus database (Bankscope). All calculations were performed in SPSS 23.

This research adopts Beaver's t-5 approach and looks back as many as five years before a declared bankruptcy, which corresponds to the usual praxis of conducting fundamental financial analysis, as well as to the potential deterioration in business conduct even of de novo, small banks with higher failure rates, when compared to established banks [23]. Thus, the t is the year in which a commercial bank bankrupted; financial ratios and values for the bank asset size were taken for the active and bankrupt banks for the years t to t-5.

The most famous early warning system of bank failures, i.e. the US banks' supervisory rating system CAMELS approach, was adopted. The indicators used to represent each of the six CAMELS groups of financial indicators are disclosed in Table 1. They were selected following the standard literature on the determinants of bank bankruptcies, preliminary results of the test equality group of means, as well as the highest data availability criterion. Selected variables mostly correspond to the ones employed in [23], [19], [4], [8], [20], [2] and somewhat alternative approximations discussed within Mayes and Stremmel [22]. There is no problem of multicollinearity between those variables, as the Pearson's correlation never exceeded 0.8. The correlation matrices and descriptive statistics for each observed year are available upon request. The number of explanatory variables is reasonable as most of the related literature witnesses the significance of a few variables (up to ten) for the bank failures prediction. Their expected impact on bank bankruptcy has a stronghold in the reviewed literature on the determinants of bank failures/bankruptcy, but, due to paper size restrictions and generally its topic, empirical background summarized only the results for solvency ratios (C). In short, higher asset quality (A), better cost management (M), higher overall profitability (E), balanced liquidity management strategy (L), and diversified activities achieved via size effect (S) diminish bank bankruptcy chances. Although not taking into consideration the capital adequacy ratio or Tier 1 capital indicator in the period of economic stability can be the critics of this study [22], certain authors, e.g. [1], already confirmed that they might not be good predictors or indicators of bank financial health.

CAMELS	Variables	Interpretation	Expected impact on bank bankruptcy
C – capital adequacy	E_A (equity to assets) E_L (equity to loans)	Leverage ratio Approximation for the capital adequacy ratio	- (closer to bankruptcy) + (distant from bankruptcy)
A – asset quality	LLR_NIR (loan loss reservations to net interest revenues)	Credit risk / asset quality indicator	+
M – management competence and expertise	C_I (cost to income) NONINTEXP_A (non-interest expense to assets)	Cost efficiency	+
E – earning ability and strength	ROA (return on assets)	Overall bank profitability	-
L - liquidity	L_A (loans to assets) L_D (loans to deposits) LIQ_DEP (liquid assets to deposits)	Asset liquidity ratio Self-financing ratio Liquidity coverage of deposits	- + -
S – sensitivity to market risks	NIM_AVG (net interest income to average assets) log A (logarithm value of bank assets)	Interest rate risk indicator Overall sensitivity to market risks and diversification opportunities / bank size (too-big-to-fail issue)	-/+ -

Table 1: *Explanatory variables*

Logistic regression was employed in many studies on bank bankruptcy [7], [9], [4], [29], [25], [21], [1]. Besides the aforementioned method, the discriminant analysis is also usually adopted to predict bank failures, e.g. [8]. However, recent evidence provided by Affes and Hentati-Kaffel [2] speaks in favour of employing logistic regression over discriminant analysis. In addition, based on the Bellovary et al. literature survey, logit analysis is used in 21% of studies published between 1930 to 2004 in the area of bankruptcy prediction for various industries and financial institutions [8]. Besides bankruptcy predictions, logistic regression is/can be quite useful for the development of credit scoring models and thus credit risk management, but also for solving some other empirical issues elsewhere. For instance, revealing the determinants and probability of achieving a certain outcome such as buying/contracting some product/service or even for predicting some medical conditions (e.g. heart attack chances, getting cancer, fatal consequences after receiving some drugs or vaccine, successful recovery, etc.). In this case, logistic regression was adopted to conclude the determinants of bank bankruptcy in the EU-15. The logistic regression model is defined in the following way [30]:

$$ln\left(\frac{P(bankruptcy)}{1-P(bankruptcy)}\right) = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \cdots + \beta_k \cdot X_k \tag{1}$$

where P is the probability of a bankruptcy given the independent or predictor variables X_1, X_2, ... X_k. The dependent variable is a binary or logit variable, which takes value 1 for the bankrupt banks, and value 0 for the active banks in a certain year. Regression coefficients are presented with β, where β_0 is a constant term, and β_1, β_2, ... β_k are estimated coefficients of the predictor variables.

All estimations were obtained via the backward stepwise elimination method. Adopting such an approach rather than enter or forward logistic regression method decreases the chances for easily eliminating potentially significant predictors. To be more precise, enter method forces the simultaneous entrance of all the predictor variables in the model, while the forward method enables gradual adding of significant predictors in the model, both at 0.05 significance level for each variable. The criterion for eliminating model variables is set at a 0.10 significance level when the backward stepwise method is adopted.

The backward stepwise method of logistic regression was applied for each observed year and for two distinct models – the one without the bank size variable and the one with that variable as bank size is an important predictor of bank survival/bankruptcy. Namely, larger the bank, lower the bankruptcy chances due to the too-big-to-fail phenomenon. Nevertheless, when the logistic regression is performed for the full sample of approximately 430 banks, out of which only up to 10% were bankrupt banks, there is a low sensitivity (5-10%), and very high specificity, which means that the model classifies active banks in an appropriate way, but that the same does not hold for the bankrupt banks. Thus, a decision was made to embrace a subsample approach i.e. to compose a new sample that consists of all bankrupt banks in a certain year and of approximately the same number of randomly selected active banks in that year (up to 50 banks). However, some data were missing for the randomly selected banks and it turned out that a slightly larger number of bankrupt banks was in the data sample. Tables 2 and 3 present the results of the logit analysis of subsamples, following the previous logic of (non)adopting the bank size variable.

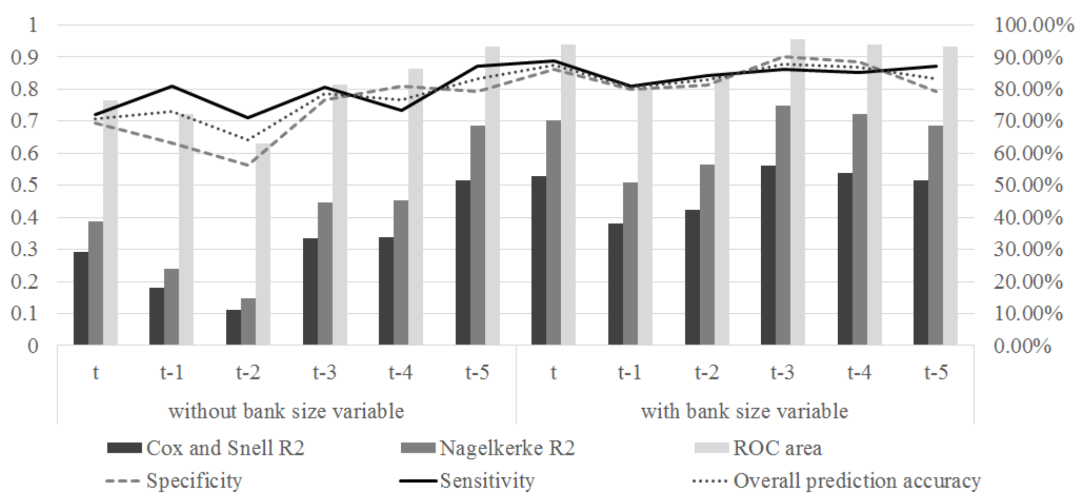

Figure 1: *A comparison of selected model results – with and without bank size variable.*

When compared to the results of the full sample testing (available upon request), the sub-sample approach leads to lower specificity and overall prediction accuracy, but higher sensitivity, i.e. predicting bankrupt banks. Furthermore, adopting bank size as an explanatory variable additionally improved the results of the baseline model (Figure 1).

Variable	t	t-1	t-2	t-3	t-4	t-5
E_A						0.169*
E_L	-0.006*				0.043***	
LLR_NIR		0.008*		0.039***	0.021*	0.126***
NONINTEXP_A	0.393***			0.339*		-1.495**
C_I		0.015*				0.116***
ROA						
L_A	-0.057***	-0.032***	-0.030***	-0.152***		-0.099***
L_D				0.051**		
LIQ_DEP				-0.060***		-0.036*
NIM_AVG						1.538***
Constant	1.946***	0.489	1.500***	5.543***	-1.622***	-3.328
Sample size	72	67	70	66	60	60
Number of bankrupt banks	36	37	38	36	34	31
χ^2	24.825***	13.237***	8.277***	26.788***	24.726***	43.383***
-2 Log Likelihood	74.988	78.912	88.248	64.162	57.381	39.728
Cox and Snell R^2	0.292	0.179	0.112	0.334	0.338	0.515
Nagelkerke R^2	0.389	0.240	0.149	0.446	0.453	0.687
Hosmer and Lemeshow Test	0.546	0.196	0.698	0.682	0.040	0.547
Specificity	69.40%	63.30%	56.30%	76.70%	80.80%	79.30%
Sensitivity	72.20%	81.10%	71.10%	80.60%	73.50%	87.10%
Overall prediction accuracy	70.80%	73.10%	64.30%	78.80%	76.70%	83.30%
ROC area	0.765***	0.721***	0.631**	0.816***	0.862***	0.931***

*** 1% level, ** 5% level, * 10% level

Table 2: *The results of logistic regression for the baseline model – subsample approach*

Namely, the average value of the Cox and Snell R Square in the estimated models with the bank size variable was 0.4905 or 49.05% (in models without logA it was 0.295 or 29.5% respectively), while the Nagelkerke R Square was 0.6558 or 65.58% (in models without logA it was 0.394 or 39.4% respectively). Cox and Snell R Square and Nagelkerke R Square measure the relationship between model variables and default prediction, where the higher values indicate better model fitting. In addition, the hit-rates recorded higher values when the bank size variable was added to the model, with a mean value of almost 85%, when compared to 74.5% for the models without logA. When the bank size variable was adopted, the classification accuracy was on average 84.2% for active banks (specificity) and 85.45% for bankrupt banks (sensitivity). Models without bank size correctly classified 70.97% of healthy banks and 77.6% of bankrupt banks in the t to t-5 period. In all the estimated cases, the area under the ROC curve was higher than the critical value of 0.5, which means that models have a good (0.7-0.8), very good (0.8-0.9) or excellent (0.9-1.0) discriminatory power to distinct active and bankrupt banks. However, for the estimations incorporating the bank size, the mean value of the ROC curve was 0.9018, while it was 0.7877 for those without bank size. Other model fitting measures such as Chi-square ($\alpha < 0.05$) and Hosmer and Lemeshow test ($\alpha > 0.05$) additionally confirm the estimates' validity.

Variable	t	t-1	t-2	t-3	t-4	t-5
E_A	-0.081*	-0.061**				0.169*
E_L	-0.012			-0.007*	0.032**	
LLR_NIR	0.010*			0.041**	0.049**	0.126***
NONINTEXP_A						-1.495**
C_I					-0.047**	0.116***
ROA						
L_A		-0.031**	-0.047**	-0.198***	-0.073**	-0.099***
L_D	-0.018***			0.064*		
LIQ_DEP	0.033***		-0.030*	-0.090***	-0.069**	-0.036*
NIM_AVG						1.538***
LogA	-1.856***	-1.237***	-1.542***	-1.964***	-1.725***	
Constant	24.976***	18.767***	24.101***	35.377***	30.792***	-3.328
Sample size	72	67	70	66	60	60
Number of bankrupt banks	36	37	38	36	34	31
χ^2	53.918***	32.171***	38.395***	54.333***	46.231***	43.383***
-2 Log Likelihood	45.895	59.978	58.130	36.617	35.877	39.728
Cox and Snell R^2	0.527	0.381	0.422	0.561	0.537	0.515
Nagelkerke R^2	0.703	0.510	0.564	0.750	0.721	0.687
Hosmer and Lemeshow Test	0.714	0.437	0.991	0.383	0.971	0.547
Specificity	86.10%	80.00%	81.30%	90.00%	88.50%	79.30%
Sensitivity	88.90%	81.10%	84.20%	86.10%	85.30%	87.10%
Overall prediction accuracy	87.50%	80.60%	82.90%	87.90%	86.70%	83.30%
ROC area	0.940***	0.804***	0.843***	0.954***	0.939***	0.931***

*** 1% level, ** 5% level, * 10% level

Table 3: *The results of logistic regression of the baseline model with bank size variable – subsample approach*

There are slight differences in the obtained results of explanatory variables impact and significance between the baseline model and the one with the bank size variable. Thus, a discussion of research findings concentrates on the better-fitted models i.e. those with the logA (Table 3).

It is evident that a lower capital ratio (E_A) signals increased chances for bank bankruptcy one year prior to such an event (at 5% significance level) and vice versa. This finding is equivalent to most of the reviewed surveys in section 2. However, five years before the failure, the opposite impact was recorded, which means that banks having sizeable capital holdings certainly build them up for the asset growth and risk accumulation purpose (Figure 2), which is in line with the capital buffer theory [24]. Imprudent and speedy growth enlarges the odds for bank bankruptcy, directly through poor business achievements and indirectly via the meltdown of bank solvency due to incapability to rebuild bank capital in a time lag, e.g. [15], [29]. Nevertheless, due to a marginal impact (at 10% level) of the solvency ratio for the t and t-5, the H-1 hypothesis (H-1: Higher bank capital increases the chances for bank survival in the year preceding the bankruptcy, but also increases the chances for bank bankruptcy several years prior to bankruptcy) is accepted with caution. Comparable findings regarding the distinct connection of capital ratios with bank failures, several years prior to troubles (positive linkage) and closer to the failure moment (negative linkage), are demonstrated by Cole and White [9] for US commercial banks in the pre-global financial crisis period and during its outbreak (2007/2008).

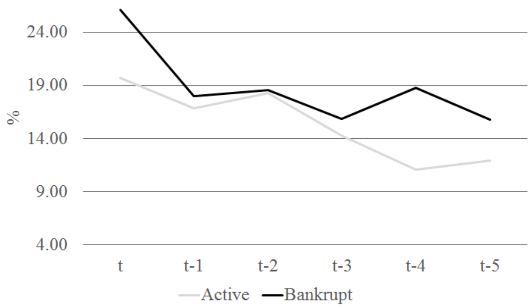

Figure 2: *Mean values of E_A.*

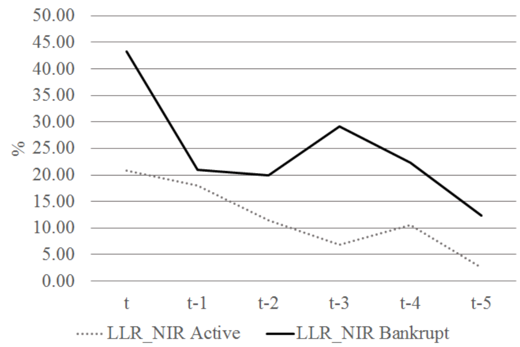

Figure 3: *Mean values of asset quality variable (LLR_NIR).*

Poor asset quality (LLR_NIR) explains bank bankruptcy several years before and in the year of bankruptcy occurrence (Figure 3). Higher loan loss reservations usually mirror higher credit risk [1], loan quality deterioration with a consequent cosmetic regulatory capital enlargement [25], and signal a higher probability of bank default [4], [1], [25], [8], rather than representing conservative provisioning policy, being a source of strength against subsequent losses, and having negative correlations with bank failures [9], [21]. Furthermore, a higher share of loans in the asset portfolio (L_A) speaks in favour of bank survival, as in e.g. [8], [20], and confirms the stability in its core activity of approving loans (Figure 4). This means that such a bank: 1) embraces profit opportunities from the real economy and supports its borrowers by performing its credit function, 2) does not have significant loan charge-offs, which decrease the ratio, which altogether confirms its reasonable credit risk-taking policy, 3) does not store excessive asset liquidity, nor is involved in some riskier securities holdings. In addition, such a bank might rely more on the long-term wholesale funding (for which a good bank credit rating is a must), which is in line with the negative impact of the loan to deposits (L_D) ratio for the bankruptcy occurrence. Negative results for the asset liquidity to deposits ratio (LIQ_DEP) for most of the observed period confirm once again the importance of adequate liquidity management for bank survival or the so-called balanced liquidity management strategy, which means maintaining some liquidity stored in assets and having some long-term wholesale funding. However, in the year of bank failure, the coefficient sign is positive, as comparable to e.g. [8], which is expected as only a bank with sufficient asset liquidity has a higher chance for survival when bank troubles are revealed. Borrowing liquidity on the interbank loan and deposit market is impossible in case of deterioration of bank credit capacity, for which reason finding strategic partners or having an active lender of last resort are the only way outs. In addition, a rapid increase in this indicator might be a consequence of significant withdrawal of core deposits (Figure 5) and conversion of assets into liquidity via asset fire sales. When looking at asset composition and liquidity indicators estimations, some deviations from usual theoretical expectations and empirical results are noticed. Namely, higher asset liquidity and lower credit exposure are assumed to be beneficial for bank financial health [19], [21], while wholesale i.e. unstable funding, is brought in line with increased default odds [23], [19], [9], [4], [22]. However, a dynamic approach in interpreting financial ratios is necessary, as they can be quite diverse in the years preceding the bankruptcy and rapidly change at the point of its disclosure. Furthermore, previous empirical evidence regarding the influence of some variables, such as liquidity ratios is mixed and inconclusive [8]. Based on the results from Table 2, operative efficiency indicators (NONINTEXP_A and C_I, Figure 6) also indicate lower bankruptcy chances, while having a higher net interest margin (NIM_AVG, Figure 7) is required to cover the operative and allocative (asset quality) inefficiency. Persistency and the magnitude of results for bank size (logA) impose

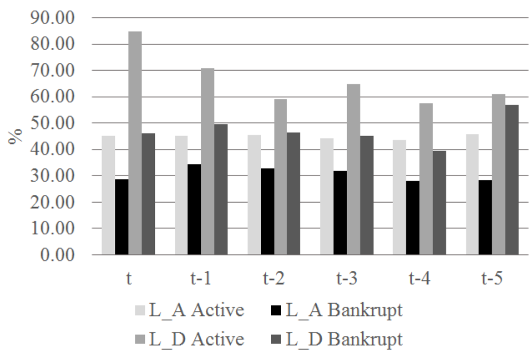

Figure 4: *Mean values of L_A and L_D.*

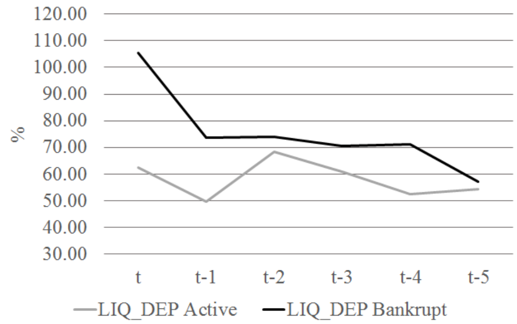

Figure 5: *Mean values of LIQ_DEP.*

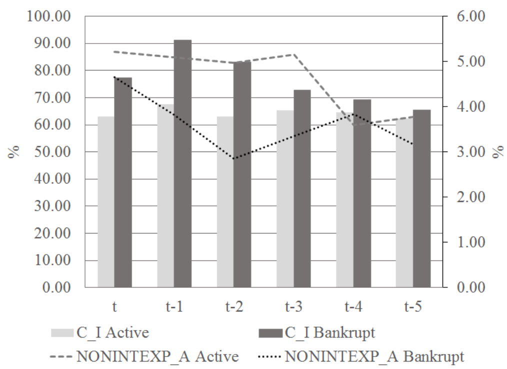

Figure 6: *Mean values of operative efficiency ratios.*

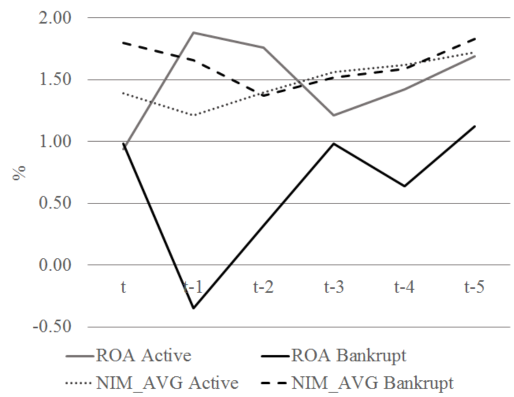

Figure 7: *Mean values of ROA and NIM_AVG*

the necessity of separate examinations of bank failures/bankruptcy for the large-sized banks and the other ones in the future, as larger banks have lower default probability [19], [1].

4. Conclusion

This cross-country analysis, which encompassed the EU-15 countries in the period prior to the global financial crisis, confirms the beneficial role of bank capital for the commercial banks' survival one year preceding the bank bankruptcy. However, the impact and predictive power of capital holdings vary between the years prior to the bank failure, as five years prior to bankruptcy occurrence it decreases the odds for the bank survival. Thus, higher capital surpluses build several years before the bank bankruptcy are obviously goaled for an imprudent bank growth in the years to follow, since poor credit quality, insufficient credit activity, and maintaining sizeable asset liquidity/deposits withdrawal are clearly connected with the bank bankruptcy. In addition, bank size variable tremendously contributes to the going concern in the business of banking. Whether the higher capital requirements are a precondition for enabling an earlier adopted strategy of granting riskier loans or the capital regulation is a trigger for the increased asset risk-taking requires additional examinations, as well as an investigation into the linkages between bank solvency and other aspects of bank management performance such as cost-efficiency and profitability. Namely, bank capital level is only a reflection of the overall banking strategy and surely is not the only contributing factor to the poor asset quality, as it is often suggested in the literature against the bank capital requirements. Therefore, more attention in early warning signals of bank failures should be dedicated to the loan portfolio structure, concentration exposures, loan growth, provisioning policies, and bank profit composition, as well as their nexus with the capital requirements level. With a more detailed approach to the quality and sustainability of bank assets and financial gains and their broader connection to the capital requirements regulation, more appropriate, fine-tuned and certainly more frequent discretionary macroprudential measures could be implemented to prevent individual bank failures and preserve the banking sector stability. Special attention should be payed to the systemically important banks, which do not bankrupt, but certainly enlarge the systemic risk. More detailed analyses of their regulatory capital, performance, and vulnerabilities should be constantly estimated, whereas the definition of failure should be sensitive to even small deteriorations in running a business. In short, a sufficient capital level makes banks robust to sudden shocks and long-lasting crisis times but cannot be a substitute or excuse for a poor business conduct. Finally, predicting bank failures might be a challenging task in the future since the loan moratorium measures imposed during the coronavirus crisis delay loan provisioning and cause recognition of losses in a time lag, which might blur the picture about the drivers of bank failures. The aforementioned points might serve as a solid path for future research, as the present one obviously suffers from insufficiently detailed financial indicators and lacks a more frequent data input instead of having year-end observations. Despite those limitations, the novelty of this study is recognized in hypothesizing diverse effects of bank capital level for their survival chances in the years preceding bank bankruptcy and at the point of its disclosure, thus confirming the validity of the capital buffer theory in bank bankruptcy predictions.

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