Finance Research Letters 51 (2023) 103411

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The role of Environmental, Social, and Governance (ESG) in predicting bank financial distress☆

Alberto Citterio [a], Timothy King [b,*]

[a] Department of Economics, University of Insubria, Via Monte Generoso, 71, 21100 Varese VA, Italy
[b] School of Accounting and Finance, University of Vaasa, Wolffintie 34, FI-65200 Vaasa PL 700,Vaasa, 65101 Finland

ARTICLE INFO

JEL codes:
G21
G33
M14
C53

Keywords:
Financial distress
Bank default
Prediction models
ESG

ABSTRACT

We analyze the predictive power of Environmental, Social, and Governance (ESG) indicators to forecast bank financial distress using a sample of 362 commercial banks headquartered in the US and EU-28 members states from 2012 to 2019. Our results demonstrate that ESG improves the predictive capability of our model to correctly identify distress. Notably, ESG strongly reduces the likelihood of misclassifying distressed/defaulted banks as healthy. Our model, which we estimate using six alternative approaches, including traditional statistical techniques, machine learning approaches, and ensemble methods, has implications for both practical implications by banking sector supervisors, as well as literature on default prediction.

1. Introduction

Bank failures, typically costlier to resolve than non-bank failures (El Diri et al., 2021), can impose significant externalities on key stakeholders, including taxpayers. Consequently, predicting bank financial distress remains a critical but difficult task for banking supervisors. Since distress is usually anticipated by several warning symptoms, better understanding of contributory factors can facilitate prompt corrective action, which can mitigate distress, prevent or reduce costs associated with failures, and improving the supervisory process by allowing supervisory bodies to better allocate resources - inter alia, by prioritizing onsite bank examinations (Flannery and Bliss, 2019).

Since the 2008 global financial crisis there has been renewed interest in examining determinants of financial distress (e.g., Soenen and Vennet, 2022), with new early-warning systems developed to detect and prevent severe bank financial distress. Yet, predictive models have almost exclusively focused on accounting variables, which are backwards looking and may represent poor predictors of future performance (Agarwal and Taffler, 2008) .[1] Consequently, several authors suggest including additional variables such as market information (Flannery and Bliss, 2019), macroeconomic indicators (Flannery, 1998; Mare, 2015) and non-financial information (Berger et al., 2016) to improve the predictive accuracy of models and the efficacy of bank supervision (Flannery and Bliss, 2019).

☆ The authors gratefully acknowledge financial support from the European Union's Horizon 2020 COST Action "FinAI: Fintech and Artificial Intelligence in Finance - Towards a transparent financial industry" (CA19130).
* Corresponding author.
E-mail address: timothy.king@uwasa.fi (T. King).

[1] Furthermore, their usefulness may be undermined by observations that in more competitive banking markets the quality of accounting information may be relatively lower (Corona et al., 2015), and by differences between book and market value of assets (Agarwal & Taffler, 2008).

https://doi.org/10.1016/j.frl.2022.103411
Received 20 July 2022; Received in revised form 10 October 2022; Accepted 10 October 2022
Available online 12 October 2022

While macroeconomic variables and market information have been tested (Männasoo and Mayes, 2009; Chiaramonte and Casu, 2017), there is only limited evidence regarding the influence of non-financial indicators on bank default probability.

In this paper, we focus on the predictive power of Environmental, Social, Governance (ESG) (ESG) indicators to forecast bank financial distress. Our focus is timely given ESG has been high on the agenda of international regulators, including, the European Banking Authority, which considers ESG disclosure important for promoting market discipline and has recently publishing binding requirements for the disclosure of ESG risks (See European Banking Authority, 2022), and given recent recommendations that ESG should be incorporated into the toolkits of regulatory authorities' supervisory mechanisms (European Banking Authority, 2021; Aevoae et al., 2022).

For a cross-country sample of European and US banks we develop a bank default prediction model that combines traditional bank-level predictors and country-level macroeconomic indicators with ESG factors. To operationalise our model, we combine operational research techniques with statistical measures to achieve better predictive performance (Demyanyk and Hasan (2010). We estimate our model using three broad alternative approaches: statistical methods, machine learning methods, and ensemble methods, which facilitates testing the robustness of our model across different techniques used by banking supervisors. By way of preview, our main results support the inclusion of ESG indicators alongside traditional predictors in bank default models.

Theoretically, ESG could impact bank default risk through both direct and indirect channels (Wu and Shen, 2013). From a stakeholder theory perspective, high ESG commitment could be indicative of improvements in bank transparency and greater support for stakeholders, whereas low ESG performance could signal a lack of commitment to minority stakeholders, including bondholders (Azmi et al., 2021). These signals, likely important from a reputational perspective, may allow high ESG banks to attract more deposits and loans than low ESG peers (Wu and Shen, 2013). Consistent with this, Simpson and Kohers (2002) document a positive link between banks' corporate social responsibility (CSR) performance and the quality of loan portfolios. Importantly, it is arguably through this reputational effect that two key channels, in cost of capital and cash flows (Azmi et al., 2021), through which ESG could affect bank risk, are rendered most salient. As argued by Azmi et al. (2021) the first, cost of capital, directly impacts the extent to which banks are financially constrained, which, in turn, impacts their ability to invest in positive NPV projects, and, thus, future cash flows. In this way, commitment to ESG should be a factor relevant for predicting bank financial distress.

Our study makes several contributions. First, it complements recent literature examining relations between ESG and bank risk (Chiaramonte et al., 2021; Aevoae et al., 2022). This literature finds that higher ESG ratings are associated with lower bank default risk (Chiaramonte et al., 2021) and systemic-wide distress (Aevoae et al., 2022). We add to this literature by demonstrating the usefulness of ESG in models used to estimate bank default.

Second, we contribute to the recent literature on bank default prediction (Mare, 2015; Chiaramonte et al., 2016; Carmona et al., 2019; Petropoulos et al., 2020). While there has been recent interest in ESG, given its potential to enhance bank stability (Chiaramonte et al., 2021), our study is the first to incorporate ESG factors in a model to predict bank financial distress. In doing so, we speak to recent suggestions that ESG should be incorporated into the toolkits of regulatory authorities' supervisory mechanisms (European Banking Authority, 2021; Aevoae et al., 2022).

2. Data and methodology

2.1. Data

As shown in Table 1, our sample includes all listed banks headquartered in the US and EU-28 member states between 2012–2019. We capture ESG performance using ESG scores from Thomson Reuters' Refinitiv Eikon (e.g., Chiaramonte et al., 2021; Aevoae et al., 2022). We also include two categories of indicators to predict distress: (1) Data from financial statements; focusing on traditional CAMEL indicators that capture credit, operational and liquidity risk, which are highly correlated with distress (Männasoo and Mayes, 2009; Chiaramonte et al., 2016; Chiaramonte and Casu, 2017; Carmona et al., 2019; Petropoulos et al., 2020); (2) annual GDP growth and inflation as proxies for macroeconomic conditions, and the Herfindahl-Hirschman index, and total domestic assets of banks divided by country GDP as indicators of banking sector competition and structure, respectively (Chiaramonte et al., 2016; Chiaramonte and Casu, 2017; Chiaramonte et al., 2021).

2.2. Methodology

To build our predictive model we first specify Z-score as our dependent variable and preferred definition of bank financial distress. Commonly used to measure solvency risk (e.g., Laeven and Levine, 2009; Delis et al., 2011; Chiaramonte et al., 2016), Z-score can be interpreted as the number of standard deviations below the mean a bank's profits have to fall before its equity becomes negative. It is computed as[2,3]:

[2] We calculate the standard deviation of ROA and each average for rolling five-year time windows of five years.

[3] For robustness we also employ alternative definitions of z-score: $Z - score_2 = \frac{mean(ROA)+mean(Equity/Total\ Assets)}{\sigma(ROA)}$ and $Z - score_3 = \frac{mean(ROA)+mean(Equity/Total\ Assets)}{\max\limits_{T_{-5}<t<T}(ROA_t) - \min\limits_{T_{-5}<t<T}(ROA_t)}$. Results remain qualitatively similar.

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variables:					
Z-score	1611	3.94	1.01	0.51	6.86
Predictive variables (CSR variable):					
ESG	1611	42.87	19.73	3.97	95.02
Predictive variables (Accounting variables)					
ETA (%)	1611	10.50	4.10	2.68	27.95
TLTA (%)	1611	62.20	20.19	0.07	111.13
NPL (%)	1611	4.12	7.56	0.00	95.04
CIR (%)	1611	62.58	13.58	30.05	106.40
ROA (%)	1611	0.92	1.33	-7.15	16.55
CDTA (%)	1611	63.89	20.21	3.20	87.99
NIOR (%)	1611	35.42	21.84	0.53	100.37
Predictive variables (Macroeconomic variables)					
GDP (%)	1611	2.06	1.83	-9.13	25.16
INF (%)	1611	1.59	1.01	-1.74	5.65
HHI	1611	5.95	3.85	2.45	38.80
TAGDP (%)	1611	188.20	140.12	51.02	818.30

The table shows descriptive statistics (mean, maximum, minimum, and standard deviation) of dependent variables, and predictive variables for the full sample of 362 commercial banks headquartered in 19 countries (representing 88% and 85% of the US and EU banking sectors, respectively), for a total of 1611 firm-year observations. ESG is the environmental, social and governance score provided by Thomson Reuter. ETA is the ratio of total equity to total assets. TLTA is the ratio of total loans to total assets. NPL is the ratio of non-performing loans to gross loans. CIR is the ratio of operating expenses to operating income. ROA is the ratio of net income before taxes to average assets. CDTA is the ratio of customer deposits to total assets. NIOR is the ratio of non-interest income to net operating revenues. GDP is the annual growth rate of real gross domestic product. INF is the inflation rate. HHI is the sum of each bank's squared markets share in a country. TAGPD is the ratio of domestic assets of banks to country's GDP. All control variables based on accounting data (ETA, TLTA, NPL, CIR, ROA, CDTA, NIOR) are winsorized at the 1% of each tail.

$$Z - score = \frac{ROA + (Equity/Total\,Assets)}{\sigma(ROA)} \tag{1}$$

We normalize Z-score so that it equals one if bank i experiences financial distress in period t, and zero otherwise. Since there is no commonly accepted threshold that distinguishes healthy from distressed banks, we systematically run each model (Eq. (2)) numerous times to test the predictive ability over alternative thresholds. In our baseline model we define financial distress as observations below the 5th percentile of the empirical probability distribution of the Z-score. We then employ alternative thresholds from the 10th percentile to the 95th percentile (in increments of five).

Our predictive model is:

$$D_{i,t} = \beta_0 + \beta_1 X_{i,t-1} + \varepsilon_{i,t-1} \tag{2}$$

where $D_i = 1$ if an observation resides below the nth percentile of the empirical distribution of the Z-score, and $D_i = 0$ otherwise. X_i represents a vector of one-year lagged predictor variables (defined in Table 1), and ε_i is the normally distributed error term with zero mean.

There is no unanimous consensus regarding the best model. Although AI techniques require fewer assumptions and allow nonlinear functions to be approximated, determination of parameters is often complex and arbitrary. Moreover, configuration and development of technically sophisticated methods is time consuming and interpretations of the contribution of predictors is sometimes complex. Therefore, our model is estimated using alternative techniques: statistical methods (logit and linear discriminant analysis (LDA)), AI methods ((classification trees (DT) and support vector machines (SVM)), and ensemble methods ((random forests (RF) and Xgboost). Our sample is split into two subsamples: 70% is used as a training set for identification purposes and 30% is used for model validation.

The model is then used to predict financial distress:

$$\widehat{D}_i = \widehat{\beta}_0 + \widehat{\beta}_1 X_i \tag{3}$$

where $\widehat{D}_i$ represents the expected probability of being financial distressed given the X characteristics. Classification of a bank into one of the two categories strongly depends on the probability of failure cut-off point. Typically, the standard approach assigns zero to observations where the expected probability of being financial distressed is < 0.5, and one otherwise. However, this approach may be inefficient because the cut-off may not be the cut-off that maximizes overall model accuracy. We therefore follow existing literature on bank default prediction and use the mean F-score (F_s) (Serrano-Cinca and Gutiérrez-Nieto, 2013; Le and Viviani, 2018); where optimal cut-off corresponds to the threshold that maximizes the arithmetic mean of the harmonic mean of the sensitivity (se) and positive predictive value, and the harmonic mean of the specificity (Sp) and negative predictive value. F_s is computed as:

$$F_s = \max\left(\frac{Se \times ppv}{Se + ppv} + \frac{Sp \times npv}{Sp + npv}\right) \tag{4}$$

where *sensitivity* identifies the true positive rate; *positive predictive value (ppv)* ((*negative predictive value (npv)*) corresponds to the proportion of banks correctly predicted as defaulted (healthy); and *specificity* represents the true negative rate. This method allows us to identify the best cut-off, whereby the sum of Type I and Type II errors are minimized. Higher F-score values imply a better capacity for the model to reduce incorrect classifications.

3. Results

Before examining the predictive power of ESG, in Fig. 1 we begin by providing a comparison of different predictive techniques to identify the decile of the Z-score distribution where the highest percentage of bank failures occur. It is interesting to note that while all techniques perform quite well, ensemble models outperform single classifiers.[4] Importantly, Fig. 1 indicates that the predictive ability of models decreases as the percentile increases, i.e., a higher percentage of banks are identified as distressed. This pattern implies that the Z-score is particularly suitable for identifying banks in severe financial distress. This result is in line with Chiaramonte et al. (2016), who show that the highest percentage of failure is found in the tenth decile of the Z-score probability distribution.

Next, to facilitate tests of the predictive ability of ESG for bank default we restrict our analysis to the best scenario identified in Fig. 1, i.e., the 5th percentile of the empirical distribution of the *Z*-score. We perform two different analyses: first, we compare the predictive power of models with and without the ESG score, and second, we compute and compare the overall improvement in the predictive power of models for each predictor.

3.1. Is ESG a useful predictor of bank financial distress?

Table 2 compares the confusion matrix and performance measures of our models with and without the ESG score in the fifth percentile specification.[5] The parameters refer to the out-of-sample forecasting, where 26 distress episodes were detected.

The results show that including the ESG score increases the predictive ability of models. Specifically, AUC ranges from 0.6 (the DT specification) to 2.1 points (the SVM specification), while F-score increases to a maximum of 4.1 points (Logit model). Interestingly, while the absolute increase in model predictive ability may appear at first glance modest, it is important to note that the introduction of ESG strongly reduces the likelihood of Type II errors, i.e., the risk of misclassifying distressed/defaulted banks as healthy. Although a model should provide low percentage of both Type I and II errors, when predicting bank default false negatives are far more costly than false positives (Poghosyan and Čihak, 2011; Cole and White, 2012; Chiaramonte et al., 2016). These findings have implications for practice. From the perspective of supervisors, false positive lead to additional bank examination costs for the misclassified healthy banks, but missing failures typically imply higher resolution costs or delayed resolutions. This conclusion can be primarily inferred looking at the improvement in the Sensitivity (Se) index, which reflects the true positive rate. To further buttress these findings, we also compute the adjusted F-score ($\mathrm{F-score}_2$), which allows us to weight *Sensitivity* and *Specificity*. When considering *Sensitivity* twice important than *Specificity*, results show that the average improvement of $\mathrm{F-score}_2$ is larger than the average improvement of F-score.

3.2. How does ESG compare to more traditional predictors of bank financial distress?

Having demonstrated the importance of ESG as a distinct factor, in Fig. 2 we examine how the predictive power of ESG compares to traditional predictors in our model.

The y-axis, which represents each variable's average ranking across models, is reversed so that the top variables are shown in the upper right corner. Although this may not provide a comprehensive description of the contributions, it shows general trends and provides a useful basis for interpretation. Unsurprisingly, the NPL ratio and the level of earnings are the most important predictors, while macroeconomic factors also perform well. With respect to ESG, the analysis shows that, on average, it occupies sixth position (among twelve predictors)., and is important than traditional variables such as ETA, extent of diversification (NIOR), management efficiency (CIR), and TLTA. These results help underline the usefulness of ESG for bank default prediction.

4. Conclusion

We introduce a novel bank financial distress model which incorporates ESG factors. Estimating our model using three broad alternative approaches, our main findings support the inclusion of ESG in predictive models of financial distress. Notably, inclusion of ESG strongly reduces the likelihood of misclassifying distressed banks as healthy.

Our findings have implications for bank supervisors in designing effective models to predict bank financial distress and for improving the efficacy of supervisory efforts. Specifically, they suggest that ESG factors be included as potential indicators even in advanced prediction models and empirically confirm an importance of incorporating ESG factors into regulatory authorities'

[4] For robustness, we test the predictive ability of models using alternative methods: Area under the ROC curve, Overall predictive accuracy and Youden Index (defined as sensitivity + specificity -1 (see Youden, 1950), and obtain similar results.

[5] In unreported results we take steps to address how endogenous variables could impact our results; for instance, ESG could be captured by existing variables. First, we demonstrate that correlations between ESG and other factors are low. Second, we present a two-step GMM model, whereby second and higher order lags and differences of the dependent variable are instruments, and remaining explanatory variables are treated as strictly exogenous. The result demonstrates our findings are robust from endogeneity arising from reverse causality and autocorrelation.

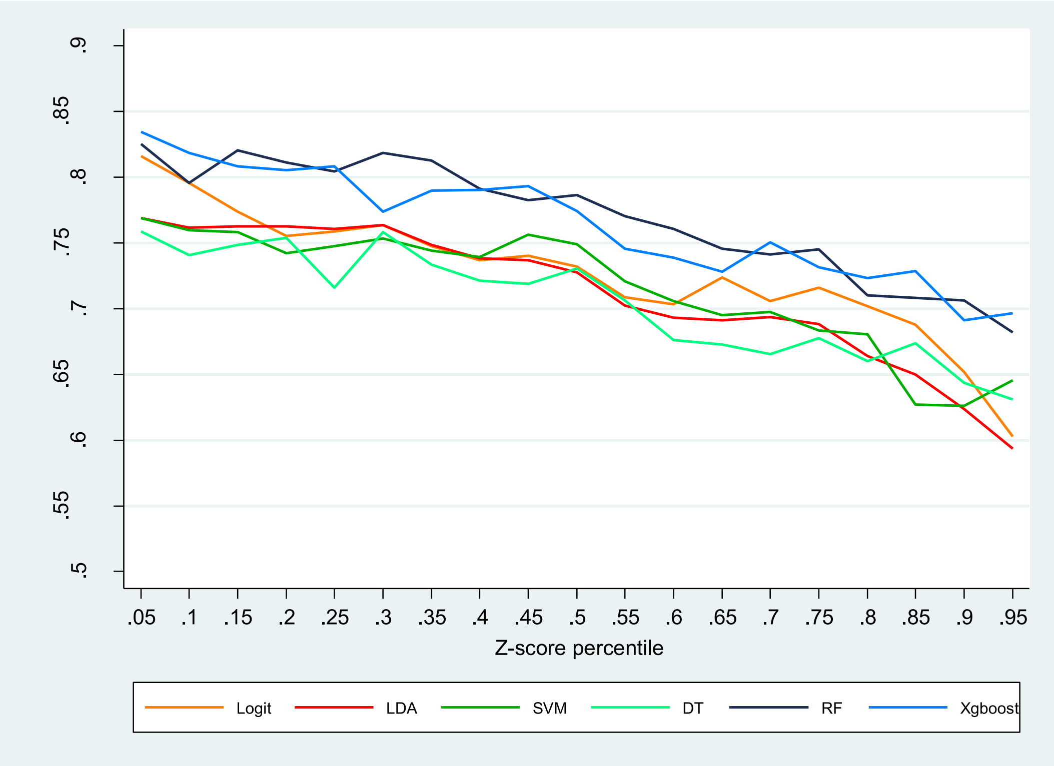

Fig. 1. Comparison of models using the F-score. The figure presents the out-of-sample predictive performance of six alternative methods based upon the estimation procedure presented in Section 2.2, which recursively tests each model using an increasing percentile of the Z-score. The approaches are compared using the F-score measure, according to which higher values indicate better predictive capacity.

Table 2
Out-of-sample performance of prediction methods with and without the ESG variable (5th percentile).

Method	Confusion Matrix				Performance measures (%)with ESG				Performance measures (%)without ESG			
	With ESG		Without ESG		F-score	Se	AUC	$F - score_2$	F-score	Se	AUC	$F - score_2$
Logit	20	6	15	11	81.7	76.9	91.8	71.9	77.6	57.7	89.8	66.0
	15	443	10	447								
LDA	17	9	13	13	77.3	65.4	92.4	64.5	75.2	50.0	90.7	63.3
	17	441	10	448								
SVM	18	8	13	13	76.9	69.2	90.7	63.8	75.2	50.0	88.6	60.8
	19	439	10	448								
DT	14	12	10	16	75.9	53.8	92.0	61.4	73.9	38.5	91.4	60.6
	9	449	4	454								
RF	18	8	15	11	82.5	69.2	93.9	68.1	80.2	57.7	92.0	65.9
	10	448	7	451								
Xgboost	21	5	16	10	83.4	80.0	93.2	76.1	81.3	61.5	91.4	72.2
	13	445	8	450								

The table shows the confusion matrix and accuracy measures for the prediction models when using the fifth percentile of the empirical probability distribution of the Z-score. For each model, we use the cut-off identified by the F-score. The confusion matrix reports the true positive, the false negative, the false positive and the true negative respectively. Sensitivity (Se) is the fraction of banks predicted to be distressed that are actually distressed. AUC is the area under the receiver operation characteristic curve. $F - score_2$ is the adjusted F-score that allow to weight Type I and Type II error: in this case, false negative is considered twice as important as false positive.

supervisory mechanisms (European Banking Authority, 2021; Aevoae et al., 2022).

CRediT authorship contribution statement

Alberto Citterio: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Timothy King:** Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing – original draft, Writing – review & editing.

Fig. 2. Variable importance across models. Fig. 2 compares the importance of each predictor across models. To facilitate comparison we consider: 1) Logit: the absolute value of the t-statistic for each model parameter; 2) LDA: the absolute value of the standardized coefficients of the LDA; 3) SVM: the variable selection algorithms optimize the objective function of variable selection, which consists of two terms that compete: goodness of fit and number of variables; 4)DT: the percentage of training set samples that fall into all terminal nodes after the split; 5) RF: the Gini index, which is a widely used metric of how close a model or variable is to the ideal prediction. This index highlights the contribution of each variable to the homogeneity of the nodes and leaves; and 6) Xgboost: the "gain" contribution of each feature to the model. It represents the average gain across all splits of each tree considered. High values denote important features for predicting the response variable. After computing each procedure, we normalize the output of each variable importance method on a 0–100 scale for comparison.

Data availability

Data will be made available on request.

References

Aevoae, G.M., Andries, A.M., Ongena, S., Sprincean, N., 2022. ESG and systemic risk. Swiss Financ. Inst. Res. Pap. (22–25).

Agarwal, V., Taffler, R., 2008. Comparing the performance of market-based and accounting-based bankruptcy prediction models. J. Bank. Financ. 32 (8), 1541–1551.

Azmi, W., Hassan, M.K., Houston, R., Karim, M.S., 2021. ESG activities and banking performance: international evidence from emerging economies. J. Int. Financ. Mark. Inst. Money 70 (3), 101277.

Berger, A.N., Imbierowicz, B., Rauch, C., 2016. The roles of corporate governance in bank failures during the recent financial crisis. J. Money Credit Bank. 48 (4), 729–770.

Carmona, P., Climent, F., Momparler, A., 2019. Predicting failure in the U.S. banking sector: an extreme gradient boosting approach. Int. Rev. Econ. Financ. 61, 304–323.

Chiaramonte, L., Liu, H., Poli, F., Zhou, M., 2016. How accurately can Z-score predict bank failure? Financ. Mark. Inst. Instrum. 25 (5), 333–360.

Chiaramonte, L., Casu, B., 2017. Capital and liquidity ratios and financial distress. Evidence from the European banking industry. Br. Account. Rev. 49 (2), 138–161.

Chiaramonte, L., Dreassi, A., Girardone, C., Piserà, S., 2021. Do ESG strategies enhance bank stability during financial turmoil? Evidence from Europe. Eur. J. Financ. 1–39.

Cole, R.A., White, L.J., 2012. Déjà vu all over again: the causes of US commercial bank failures this time around. J. Financ. Serv. Res. 42 (1–2), 5–29.

Corona, C., Nan, L., Zhang, G., 2015. Accounting information quality, interbank competition, and bank risk-taking. Account. Rev. 90 (3), 967–985.

Delis, M.D., Staikouras, P.K., 2011. Supervisory effectiveness and bank risk. Rev. Finan. 15 (3), 511–543.

Demyanyk, Y., Hasan, I., 2010. Financial crises and bank failures: a review of prediction methods. Omega 38 (5), 315–324.

El Diri, M., King, T., Spokeviciute, L., Williams, J., 2021. Hands in the cookie jar: exploiting loan loss provisions under bank financial distress. Econ. Lett. 209, 110098.

European Banking Authority. (2021). Report on environmental, social and governance (ESG) risks management and supervision. June. URL: https://www.eba.europa.eu/sites/default/documents/files/document_library/Publications/Reports/2021/1015656/EBA%20Report%20on%20ESG%20risks%20management%20and%20supervision.pdf. Accessed on 14-07-2022.

European Banking Authority. (2022). Final draft implementing technical standards on prudential disclosures on ESG risks in accordance with Article 449a CRR. January. URL: https://www.eba.europa.eu/sites/default/documents/files/document_library/Publications/Draft%20Technical%20Standards/2022/1026171/EBA%20draft%20ITS%20on%20Pillar%203%20disclosures%20on%20ESG%20risks.pdf.

Flannery, M.J., 1998. Using market information in prudential bank supervision: a review of the US empirical evidence. J. Money Credit Bank. 30 (3), 273–305.

eds Flannery, M.J., Bliss, R.R., 2019. Market discipline in regulation: pre- and post-crisis, Chapt. In: Berger, Allen N., Molyneux, Philip, Wilson, John O.S. (Eds.), Oxford Handbook of Banking, 3e. Oxford University Press, p. 23. eds.

Laeven, L., Levine, R., 2009. Bank governance, regulation and risk taking. J. Financ. Econ. 93 (2), 259–275.

Le, H.H., Viviani, J.L., 2018. Predicting bank failure: an improvement by implementing a machine-learning approach to classical financial ratios. Res. Int. Bus. Financ. 44, 16–25.

Männasoo, K., Mayes, D.G., 2009. Explaining bank distress in Eastern European transition economies. J. Bank. Financ. 33 (2), 244–253.
Mare, D.S., 2015. Contribution of macroeconomic factors to the prediction of small bank failures. J. Int. Financ. Mark. Inst. Money 39, 25–39.
Petropoulos, A., Siakoulis, V., Stavroulakis, E., Vlachogiannakis, N.E., 2020. Predicting bank insolvencies using machine learning techniques. Int. J. Forecast. 36 (3), 1092–1113.
Poghosyan, T., Čihak, M., 2011. Determinants of bank distress in Europe: evidence from a new data set. J. Financ. Serv. Res. 40 (3), 163–184.
Serrano-Cinca, C., Gutiérrez-Nieto, B., 2013. Partial least square discriminant analysis for bankruptcy prediction. Decis. Support Syst. 54 (3), 1245–1255.
Simpson, W.G., Kohers, T., 2002. The link between corporate social and financial performance: evidence from the banking industry. J. Bus. Ethics 35 (2), 97–109.
Soenen, N., Vennet, R.V., 2022. Determinants of European banks' default risk. Financ. Res. Lett. 47, 102557.
Wu, M.W., Shen, C.H., 2013. Corporate social responsibility in the banking industry: motives and financial performance. J. Bank. Financ. 37 (9), 3529–3547.
Youden, W.J., 1950. Index for rating diagnostic tests. Cancer 3 (1), 32–35.