To fail or not to fail? Assessing the microprudential efficiency of Basel III

Abstract

Using a database comprising US bank balance sheet variables covering the 2000-2018 period and the list of failed banks as provided by the FDIC, we run various models to compute banks' default probability in order to assess the microprudential efficiency of Basel III. A companion website is available to execute the associated code on a Github repository. We provide evidence that 1) capital is a stronger predictor of default than liquidity, 2) Basel III capital requirements should be set at a higher level. Having a look at the impact of the interaction between capital and liquidity on the probability of default, we indeed show that the influence of the former completely outweighs that of the latter. Concerning the impact of capital ratios on the probability of default, we provide evidence that increasing the former allows reducing the latter up to a certain point. More precisely, it seems that when the risk-weighted ratio is around 15% and the simple leverage ratio around 10%, the probability of default reaches it lowest value. These results therefore call for strengthening capital requirements while at the same time releasing the regulatory pressure put on liquidity.

Keywords: Basel III, capital requirements, liquidity regulation, bankruptcy prediction models, statistical learning, classification

JEL classification: C44, G21, G28

1. Introduction

Banking regulation has been profoundly reshaped since the 2007-08 crisis. Capital requirements have indeed been tightened, liquidity ratios added to complement them and bail-in standards implemented to prevent costly bailouts from occurring. While all these instruments are related to one or several features of the 2007-08 crisis – the tightening of capital requirements being the response to banks' massive under-capitalization *prior* to the crisis, the liquidity ratios being the response to the notorious liquidity spirals (Brunnermeier and Pedersen, 2009) that materialized at the end of the 2000s, the bail-in standards answering the need to protect taxpayers from very costly bailouts – no consensus exists concerning the optimal design of these rules and the impact of their joint-implementation. Indeed, there is no consensus concerning the optimal level of capital requirements (Dagher et al., 2020), no more consensus as to whether liquidity and capital standards are actually complements or substitutes (Clerc et al., 2022), and there is a growing fear that the current tendency to multiply the number and the complexity of rules prevents banking regulation from efficiently ensuring financial stability (Herring, 2018; Haldane and Madouros, 2012).

This paper aims at assessing the microprudential efficiency of Basel III. To do so, we build bankruptcy prediction models which are applied to a database comprising US bank balance sheet variables covering the 2000-2018 period. The objective is twofold. First, from a regulatory perspective, the purpose is to disentangle which variables, among a wide range of balance sheet variables, impact the most the probability of default and how they impact it. Second, from a methodological perspective, we aim at determining which model performs best at predicting bank default. In addition to the standard (but effective) logistic approach, the use of machine learning methods enables us to address the issue of non-linearities in the effect of regulatory ratios and to test the predictive performances of these models. More precisely, we resort to seven different models: Logit, Random Forests (RF), K-Nearest Neighbors (KNN), Gradient Boosting Classification (GBC), Histogram-based Gradient Boosting Classification (HGBC), Linear Support Vector Classification (Linear SVC) and Multi Layer Perceptron (MLP). Logit, RF, GBC and HGBC perform the best, while Linear SVC, KNN and MLP are lagging behind. The performance of the various models being established, we then resort to several machine learning interpretation tools to cast light on the regulatory questions mentioned above. A companion website is available and provides the detailed and annotated codes as well as additional results.[1] We provide evidence that:

- Capital is a stronger predictor of bank default than liquidity. When considered in isolation from each other, in mean and all things being equal, capital ratios – both the total regulatory capital ratio (TRCR) and the total equity over total assets ratio (TE/TA) – have a negative impact on the probability of default, while the liquidity ratio – liquid assets over total assets (LA/TA) – has a positive impact. Though counter-intuitive, this second result can be explained by the propensity of failing banks to panic sell their illiquid assets, which mechanically improves their liquidity *prior* to default. *Per se*, this

[1] See: Github link.

result therefore does not contradict the idea at the heart of the Liquidity Coverage Ratio (LCR). When capital and liquidity are considered in interaction, we however notice that the effect of capital on the probability of default completely outweighs that of liquidity. As a consequence, from a microprudential perspective, it may be preferable to rule the LCR out to focus on capital requirements. This is in line with a recommendation made by Thakor (2018).

- Basel III capital requirements are set at a too low level. Regarding our results in a matter of predicting default probability, statistical learning methods perform as well as the standard logistic regression. But non-linear models – such as RF – allow to identify two regimes: one characterized by a low capitalization associated with a high probability of default, the other characterized by a larger capitalization associated with a low probability of default. More precisely, we manage to approximate the threshold values of the capital ratios above which banks enter the second regime: when the leverage ratio (TE/TA) is greater than 10% and the risk-weighted capital ratio (TRCR) is above 15%, banks enter the low-risk-of-default regime. Increasing capital requirements above these two thresholds is shown to have no further impact on the probability of default. As a consequence, we recommend setting the leverage ratio at 10% and the risk-weighted capital ratio at 15%, which is above what Basel III recommends, but consistent with Dagher et al. (2020). Increasing capital requirements to these levels would not hamper banks' activities. On the contrary, as shown by Durand and Le Quang (2022), this would actually have a positive impact on banks' return on assets (ROA). The only adverse effect would be on banks' return on equity (ROE), which would indeed decrease. In other words, setting the capital ratios to these levels would generate a benefit (a significant decrease in banks' probability of default) whose cost is a private cost supported only by shareholders. Notice that these would obviously benefit from the lowering of the probability of default, which eventually could compensate the ROE's decrease.

These policy recommendations have recently been reality checked. Indeed, both the failure of Silicon Valley Bank (SVB) and the difficulties encountered by Credit Suisse in March 2023 comfort the two points that have just been developed. 1) Credit Suisse's LCR was more than met in March 2023 since Credit Suisse's high quality liquid assets covered more than 150% of the expected outflows. Nonetheless, this did not prevent the bank from bankrupting. In fact, in the age of social media the rate at which depositors withdraw their deposits when they start questioning the solvency of their bank exceeds by far the stress scenarios on which the computation of the LCR is based. As a consequence, even though SVB was not subjected to the LCR, such instrument would have hardly been sufficient to deal with the massive outflows of deposits faced by the bank. During contemporary bankruns, social media indeed act as bankrun catalyst (Cookson et al., 2023) so that cash demand appears as unlimited, which questions the relevance of an approach based on the constitution of a limited reserve of liquid assets. On the contrary, the stress should be put on banks' solvency. 2) In this respect, both SVB's and Credit Suisse's capital ratios were below the levels put forward in this paper: in 2022, Credit Suisse's CET1 leverage ratio was slightly greater than 5% (SVB: around 8%), while its risk-weighted ratio slightly above 14% (SVB: around 16%).

The rest of the paper is organized as follows. The next section reviews the literature to which this paper contributes. Section 3 offers some details on the models that are used in the paper. Section 4 describes our database. Section 5 presents the main results. Robustness checks are provided in section 6 and section 7 concludes.

2. Literature review

2.1. Determinants of bank default

The literature on the determinants of bank default seeks to exhibit which variables are the best predictors of default. Since information on bank default is hard to obtain, part of the literature on this topic resorts to proxies. The main proxies used are the z-score (Demirgüç-Kunt and Huizinga, 2010; Laeven and Levine, 2009), the NPL ratio (Berger and DeYoung, 1997; Delis and Staikouras, 2011), the CDS spreads (Alter and Schüler, 2012) or the distance to default (Eichler and Sobanski, 2016).

When information on bank default is available, the bankruptcy prediction problem consists in a simple classification problem. Such a problem can be solved either by resorting to a statistical approach or to an intelligent approach (Ravi Kumar and Ravi, 2007). Statistical methods include well-known logistic regressions and are widely used to deal with classification problems, including bankruptcy prediction for firms (Jones and Hensher, 2004) and for banks (Martin, 1977; Kolari et al., 2002; Imbierowicz and Rauch, 2014). Intelligent methods consist in machine learning techniques such as for instance neural networks or random forests. Specifically, neural networks are largely used in the bankruptcy prediction literature (Ravi Kumar and Ravi, 2007) and are often shown to perform better than logistic regressions (Tam and Kiang, 1990; Tam, 1991; Salchenberger et al., 1992; Petropoulos et al., 2020). Fewer papers resort to random forests to predict firms' failures (Zoričák et al., 2020) or banks' failures (Petropoulos et al., 2020).

The main challenge associated with bankruptcy prediction is that, by definition, bankruptcies are very rare events. Datasets are thus severely imbalanced with one class (that of bankrupted banks) far less represented than the other (that of non-bankrupted banks). There are several ways to deal with imbalanced datasets: either under-sampling or over-sampling (or mixing the two). Under-sampling aims at reducing the size of the majority class to match that of the minority class. It therefore has the inconvenience to delete information, but is in general less computationally demanding than over-sampling. Over-sampling consists in balancing class distribution by replicating items in the minority class, either by exactly replicating some randomly selected items found in the minority class – that is the logic behind Random Oversampling With Replication (ROWR) (Zhou, 2013) – or by creating new items through the Synthetic Minority Oversampling Technique (SMOTE) proposed by Chawla et al. (2002). If under-sampling could sometimes be preferred to over-sampling when the dataset is weakly imbalanced (Zhou, 2013), there is a consensus in the literature that SMOTE is the best option for severely imbalanced datasets (Chawla et al., 2002; García et al., 2012; Zhou, 2013; Haixiang et al., 2017).

The literature on the determinants of bank default has reached a consensus around several financial ratios that are considered as the main determinants of defaults. Those ratios are the rationale behind the computation of the widely used z-score (Altman, 1968; Altman et al., 1977) and behind the CAMELS ratings.[2] In this respect, the literature provides evidence that capital greatly influences the probability of default (Berger and Bouwman, 2013; Parrado-Martínez et al., 2019). In addition to these financial ratios, the literature identifies several structural and environmental factors that significantly impact the default risk. These factors consist, for instance, in the monetary policy led by the central bank (Soenen and Vander Vennet, 2021, 2022) or in specificities related to national politics (Eichler and Sobanski, 2016). Ravi Kumar and Ravi (2007) provide an exhaustive review of the variables found as predictors of bank default in papers published from 1968 to 2005.

2.2. Capital requirements

Since capital is a strong determinant of bank default, regulators have soon emphasized its role as a prudential instrument by designing capital requirements constraints. There however is no consensus concerning the level of such constraints. Indeed, the banking industry opposes any strengthening of equity requirements on the basis that they would unambiguously increase their funding cost and thus force them to increase their loan rates, which would impose a cost on society as a whole. Gambacorta and Shin (2018) provide evidence that contradicts this argument. They indeed show that an increase of 1 percentage point in the equity ratio (equity over total assets) yields a decrease of 4 basis points in the cost of debt for a sample of banks located in the G10 countries. Kashyap et al. (2010) provide evidence that, in the long-run, the impact of "substantially heightened" capital requirements on loan rates is expected to be weak. They indeed find that a 10 percentage-point increase in the capital requirement increases loan rates between 25 and 45 basis points. As Admati et al. (2013) point it, the social cost associated with an increase in equity requirements is thus expected to be low. In the same vein, Durand and Le Quang (2022) provide evidence that an increase in the equity ratio has a positive impact on the return on assets (ROA), but a negative impact on the return on equity (ROE) above a threshold of 8% of the equity ratio. They conclude that the sole cost associated with an increase in equity requirements above this threshold is a private cost supported by shareholders.

The question of what exactly is the value of the optimal capital ratio is however rarely explicitly addressed by the literature. Oddly enough, while under Basel II the minimum ratio of risk-weighted Tier 1 capital was set at 4% and the minimum total risk-weighted capital ratio (i.e. Tier 1 plus Tier 2) at 8%, the Basel Committee never provided any rationale for these minimum levels (Herring, 2018). Similarly, no economic rationale is provided for the revised minima put forward by Basel III. Recall that these constrain banks to comply with the following ratios: a minimum 8.5% Tier 1 ratio made at least of 7% of CET1 capital and a minimum Tier 1 leverage ratio (i.e. not risk-weighted) of 3%. Miles et al. (2013) provide evidence that these requirements are not optimal. They indeed show that the optimal amount of capital is likely to be at least twice as great as that defined by Basel III. More precisely, they conclude that a ratio of equity over RWA of 20% is optimal, which corresponds to a financial structure resting on 90% to 93% of

[2] Capital adequacy, Assets quality, Management, Earnings, Liquidity, and Sensitivity constitute the six factors used by regulatory authorities to classify financial institutions according to their soundness.

debt and 7% to 10% of equity. Setting minimum equity requirements between 7% and 10% of total assets would therefore allow banks to face crises more efficiently without hampering their activity. The idea that Basel III capital requirements lie under their optimal values is supported by the literature. Using a DSGE model, Karmakar (2016) indeed shows that doubling the equity ratio from 8% to 16% is welfare-improving. Egan et al. (2017) show that below the $15-18\%$ range, capital requirements are insufficient so that loss of welfare and financial instability arise. Barth and Miller (2018) find an optimal equity ratio of 19%, which corresponds to a risk-weighted ratio around 25%. The "seawall approach" proposed by Dagher et al. (2020) yields a more conservative optimal risk-weighted ratio lying between 15% and 23%. Based on an empirical study concerning the euro area, Soederhuizen et al. (2021) recommend to set the minimum risk-weighted capital ratio at 22%. Mendicino et al. (2021) also find that Basel III capital requirements are set at a too low level and recommend setting them at 15%.

2.3. Interaction between liquidity and solvency risks

While the empirical literature on the determinants of bank default provides great insight concerning the main determinants of the default risk, it does not allow to precisely disentangle how those determinants interact. In particular, despite the stress put on the liquidity risk after the 2007-08 crisis (Acharya and Mora, 2015), few empirical papers have managed to show how liquidity and solvency risks interact. From a theoretical point of view, this interaction lies at the core of the seminal paper by Diamond and Dybvig (1983). These authors indeed manage to show that the liquidity risk, when modeled as early withdrawals of cash by depositors, can sometimes precipitate the failure of an otherwise solvent bank. If such a run is rendered far less likely in a context where most advanced economies have implemented a deposit insurance scheme, the Diamond-Dybvig framework can nonetheless be adapted so as to model the destabilizing consequences of the strong reliance of banks on very-short term debts (Morris and Shin, 2016).

The empirical literature on the interaction between the solvency and the liquidity risks is rather thin. Imbierowicz and Rauch (2014) explore the relationship between these two risks based on a sample of US banks (4046 non-defaulting banks and 254 defaulting banks) between 1998 and 2010. They show that, if taken separately these two risks always impact the probability of default, the impact of their interaction greatly varies depending on banks' probability of default. DeYoung et al. (2018) provide evidence that capital and liquidity are seen as substitutes by small banks. The idea is that these banks tend to improve the liquidity of their assets when their capital deteriorates: to prevent runs from happening, banks that witness a depletion of their capital switch away from illiquid assets to improve their short-term ability to raise liquidity. The authors therefore conclude that the liquidity risk is naturally mitigated by capital constraints at the level of small community banks, which justifies their exemption from the Basel III liquidity standards.

Disentangling the respective roles of liquidity and capital in banking crises is therefore of the utmost importance for banking regulation. Indeed, depending on the relationship between liquidity and capital, the joint implementation of capital ratios and liquidity ratios could either be seen as a step toward a more stable banking system or as a sub-optimal complexification of banking regulation. However, whether liquidity and capital standards are complements or substitutes to one another is a question that has not reached a consensus in the literature (Clerc et al., 2022). Another way to phrase the issue is to inquire which of the liquidity and of the solvency risks is to be understood as the consequence of the other. In other words, if liquidity dry-ups are shown to sometimes precede capital depletion in banking crises, then adding liquidity constraints to already existing capital constraints makes total sense. On the contrary, if liquidity difficulties only occur when banks are insufficiently capitalized, then the solution is to increase capital requirements and not to implement liquidity ratios. In that case, such ratios only reinforce the complexity of banking regulation without dealing with the main issue at stake: under-capitalization. Empirical evidence seems to suggest that, during the 2007-08 crisis, liquidity dry-ups were most of the time the mere consequence of insufficient capital levels (Thakor, 2018). Indeed, using transaction-level data on short-term unsecured certificates of deposit in Europe between 2008 and 2014, Pérignon et al. (2018) provide evidence that, even if many banks suffered funding dry-ups, no market-wide freeze occurred during this period. Best-capitalized banks actually increased their short-term uninsured funding, while only least-capitalized banks reduced funding. Evidence therefore suggests that stronger capital requirements by themselves could have prevented liquidity dry-ups from happening.

3. Methodology

The aim of this paper is to assess the microprudential efficiency of Basel III. To this end, we propose to compute the effect of changes in the prudential ratios on the probability of bank default. We thus face a classification problem in which the main methodological issues are: (i) managing extremely rare events (few defaults, 1, against many non-defaults, 0), (ii) choosing the model that performs the best at predicting bank default, and (iii) finding interpretable machine learning tools to make (economic) sense of the predictions made by the models.

We use several models but their objective is common, that is to estimate the function f defined as:

$$y = f(X, \Theta) + \epsilon$$

where $y \in \{0; 1\}$ is the explained variable, f is the objective function, Θ the parameters of the model, X is the matrix of the explanatory variables and ϵ is the error term. The estimates of $\hat{f}$ for each model give a prediction of $P(y = 1)$, the probability of default. Keeping this in mind, the rest of this section briefly presents the main methodological aspects on which this paper is based. Specifically, the models used to predict bank failures are introduced (section 3.1), alongside with the performance measures used (section 3.2) and the interpretation tools mobilized (section 3.3).

3.1. Models

Seven models are run to predict bank failures: Logistic regression (Logit), Random forest (RF) (Breiman, 2001), Gradient boosting classifier (GBC) (Friedman, 2001), Histogram-based Gradient Boosting classifiers (HGBC) (Chen and Guestrin, 2016; Ke et al., 2017), Support vector classifier (SVC) (Boser et al., 1992), Multi-layer perceptron (MLP) (McCulloch and Pitts, 1943; Hastie et al., 2009) and K-nearest neighbors (KNN). Models are implemented in Python thanks to Scikit-learn (Pedregosa et al., 2011).

As mentioned in the literature review (see section 2.1), since the dataset we are dealing with is severely imbalanced, a strategy needs to be implemented to balance the dataset. In accordance with the literature, we implement the Synthetic Minority Over-sampling Technique (SMOTE) as introduced by Chawla et al. (2002) from Ha and Bunke (1997). SMOTE uses the k-nearest neighbors of all the instances found in the minority class (failed banks in our case) to synthesize new minority class instances: synthetic observations are created on the line between existing ones. Using nearest neighbors ensures that the distribution of the balanced sample is the same as that of the original imbalanced sample. SMOTE is used only on the train sample.

3.2. Performance

Each of the models presented above generates predictions that allow to classify banks in either of the two considered categories (i.e. failed or unfailed). To assess the performance of the various models used, we rely on the well-known confusion matrix (Hand, 2012). From this matrix, the *recall* is defined as the proportion of a given class that is properly identified and the *precision* as the proportion of predictions for a given class that actually belongs to this class. There generally is a tradeoff between recall and precision, especially when the dataset is imbalanced. Indeed, focusing only on either of the two criteria may result in selecting an actually very poor performing model. On the one hand, a model exhibiting a recall equal to 1 might correspond to a model which classifies all the observations in the class for which the recall is computed. Such a model would misclassify all the observations that actually belong to the other class and would consequently exhibit a very poor precision. On the other hand, when the dataset is severely imbalanced, a model which would consider all the observations as belonging to the majority class would necessarily exhibit a very high precision while it in fact would misclassify all the observations that belong to the minority class (failed banks in our case). In this case, the recall computed on the minority class is equal to 0.

The $F1$-score, defined as the harmonic mean of the recall and the precision, is designed to tackle this problem. However, when the dataset is severely imbalanced and when the class defined as the positive instance is the minority class, focusing on the $F1$-score tends to favor models which actually exhibit poor recalls. Using the $F1$-score as the reference measure to assess the performance of the models would therefore result in selecting models that perform well in every aspect (precision on both classes and recall on the majority class) except in predicting default (recall on the minority class), which would contradict the very purpose of bank default prediction models. To circumvent this problem, we resort to the *macro recall*, which is defined as the average between the proportion of 1 (failed banks) that is well predicted and the proportion of 0 (unfailed banks) that is well predicted. Doing so allows to tackle the precision/recall tradeoff (a model that would classify all the observations in the same class would end up with a macro recall equal to 0.5) without sacrificing the ability of the models to properly identify the failed banks (recall on the minority class). It is worth noticing that, when the classification problem is a binary problem, the area under the

ROC curve can be computed the same way as the macro recall (Fawcett, 2006; Sokolova and Lapalme, 2009; Muschelli, 2020). In that case, these two metrics are thus equal.

3.3. Interpretation

Machine learning is very often considered as a good way to build solid predictions, but as a poor way to yield economic meaningful results. However, numerous machine learning interpretation tools have recently been developed which make it possible to interpret results drawn out of machine learning models basically the same way as results coming from econometric models. Specifically, the "significativity" of the variables we are interested in can be assessed relying on Shapley values (Shapley, 1953; Strumbelj and Kononenko, 2013; Lundberg and Lee, 2017; Lundberg et al., 2020) or on permutation feature importance (Molnar, 2020). As for the nature of the impacts of the independent variables on the dependent variable, they can be assessed thanks to partial dependence plots (PDPs) (Friedman, 2000; Hastie et al., 2009) and average local effects (ALEs) (Datta et al., 2016). As Zhao and Hastie (2021) show it, PDPs can allow to exhibit causal effects between variables. In particular, when the predictive power of the model is great and when the backdoor condition is met (Pearl, 1993), such causal effects can be established.

4. Data and descriptive statistics

4.1. Data

Our sample consists in US bank balance sheet variables covering the 2000-2018 period. Data come from the FitchConnect database. Failed banks are identified thanks to the list of failed banks as provided by the Federal Deposit Insurance Corporation (FDIC). This list gathers failures of banks that were covered by the FDIC deposit insurance scheme. After data treatment for missing values, we managed to keep 23 variables (see our GitHub repository for more insights on definitions), 4707 banks among which 454 have defaulted. Table 1 displays the evolution of the number of banks and defaults per year.

Table 1: Evolution of the number of observations and defaults per year

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Nb. obs.	3866	3961	4029	4067	4076	4305	4337	4435	4516	4465
Nb. defaults	0	1	1	3	0	0	1	18	115	138

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018
Nb. obs.	4361	4291	4226	4207	4194	4198	4191	4196	4197
Nb. defaults	80	42	21	13	7	5	6	0	3

Source: Authors' calculations.

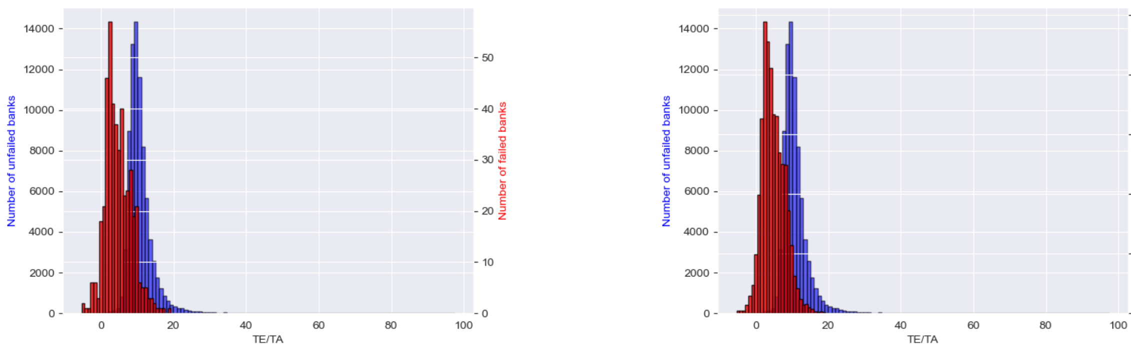
4.2. Descriptive statistics

The main purpose of the models that are presented in this paper is to classify banks, that is to separate unfailed from failed banks. We therefore focus on the characteristics of these two groups in order to exhibit significant differences. In particular, we concentrate on the following variables: total equity over total assets

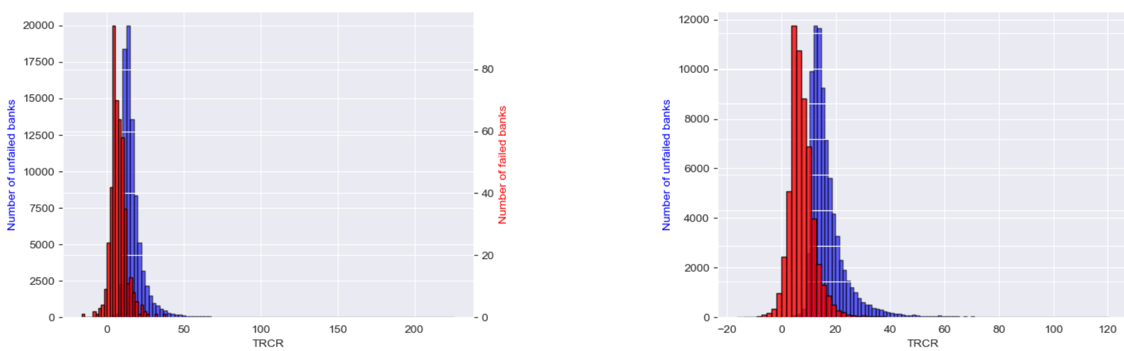
(TE/TA), total regulatory capital ratio (TRCR) and liquid assets over total assets (LA/TA). These variables account for regulatory ratios aiming at ensuring banks' solvency (TE/TA and TRCR) and liquidity (LA/TA). Variables' distributions are presented in Figure 1. In line with the CAMELS approach, we notice that better capitalized banks (i.e. banks with higher values of TE/TA and TRCR) are less likely to go bankrupt than less capitalized banks. On the contrary, there is no clear difference between failed and unfailed banks from the viewpoint of the liquidity of their asset portfolios. In fact, it seems that failed banks look slightly more liquid than unfailed banks. This unclear relationship between banks' probability of default and banks' liquidity may however be rendered intelligible keeping in mind the two contradictory mechanisms at work. On the one hand, in line with the CAMELS approach, liquid banks are less likely to go bankrupt since it is easier (less costly) for them to cope with the liquidity outflows required by their creditors.

Figure 1: Main regulatory variables' distributions before (left) and after (right) SMOTE

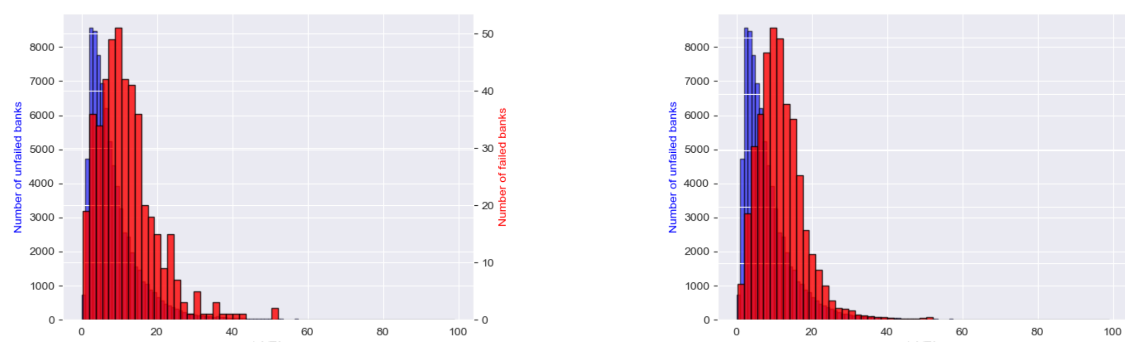
(a) TE/TA



(b) TRCR



(c) LA/TA



Source: Authors' calculations.

On the other hand, failing banks – or banks close to default – are very often constrained to panic sell their illiquid assets, which mechanically increases the liquidity of their asset portfolios *prior* to their default. As a consequence, failed banks are likely to be characterized by large LA/TA ratios because of the panic sales they may have been forced to engage in. It is moreover worth noticing that applying SMOTE to our dataset does not modify the distributions of the variables that are here presented.

5. Results

5.1. Models' performance

Let us deal first with the question of the performance of the various models we resort to. To do so, we compute the performance measures presented in the methodological section. More specifically, since the purpose of the paper is to inquire the determinants of bank default, we pay particular attention to recall. Since models can boost recall by simply over-identifying the number of failed banks, we do not exactly focus on recall but on macro recall. This latter measure is the simple average between the recalls computed for each class (failed banks, unfailed banks). In addition, in the case of a binary classification problem, this measure is equal to the area under the ROC curve (AUROC). For each model, a table provided on our companion website presents the values of the hyperparameters which maximize the macro recall. Table 2 displays the values of the recalls and macro recalls for the models. Paying attention to the macro recalls computed on the test sample, we notice that four models display scores above 88%: Logit,[3] RF, GBC and HGBC. KNN, Linear SVC and MLP are lagging behind. KNN and MLP are particularly bad at identifying failed banks (low recalls), while Linear SVC over-identifies failed banks, which explains the large recall.[4]

Table 2: Models' performance

	Logit		RF		KNN		GBC	
	Train	Test	Train	Test	Train	Test	Train	Test
Recall	84.55	82.64	90.93	80.99	100	71.90	90.73	80.99
Macro recall (AUROC)	90.12	89.13	93.74	88.63	100	82.29	93.49	88.52

	HGBC		Linear SVC		MLP	
	Train	Test	Train	Test	Train	Test
Recall	96.80	80.99	93.92	86.77	90.04	76.56
Macro recall (AUROC)	96.82	88.72	84.74	81.25	92.94	86.11

Source: Authors' calculations.

We invite the reader to consult the companion website for more information on the confusion matrices and the nature of our false positives and negatives: let's notice that, depending on the considered model, between

[3]To avoid the problems that arise when too many variables are considered in a logistic regression, only four variables are considered in the Logit: ROAA, TRCR, LA/TA and TE/TA. Notice that the performance of the model is only marginally improved when all the variables are taken into consideration.

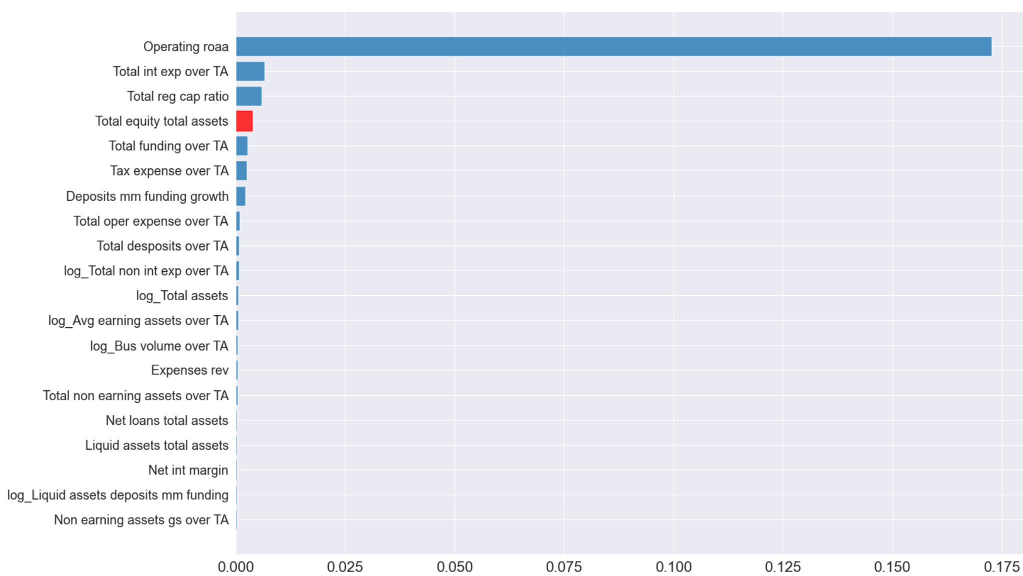
[4]Linear SVC's precision on the test sample is 1.77%.

14.61% and 18.75% of the false positives are actually previous observations of banks that do eventually go bankrupt.

5.2. Determinants of bank default

To determine which variables impact the most the probability that banks go bankrupt, we compute both the permutation feature importance (Figure 2) and the Shapley values (Figure 3). Results are only presented for RF. The results for the other models are available on the companion website. Notice that all the models yield similar results. In both figures (Figures 2 and 3), variables are ranked according to the importance of their impact on the prediction made by the model. We focus in particular on variables TRCR, TE/TA and LA/TA. We first notice that operating ROAA is the most important feature, which is consistent. In addition, in line with the CAMELS approach, we remark that capital and liquidity are most of the time significant predictors of bank default. We notice that variables associated with capital (TRCR and TE/TA) prove better predictors of default than LA/TA. This point will be further developed in section 5.4. Concerning the relative importance of TRCR and TE/TA, it seems that TRCR is a greater determinant of the probability of default than TE/TA.

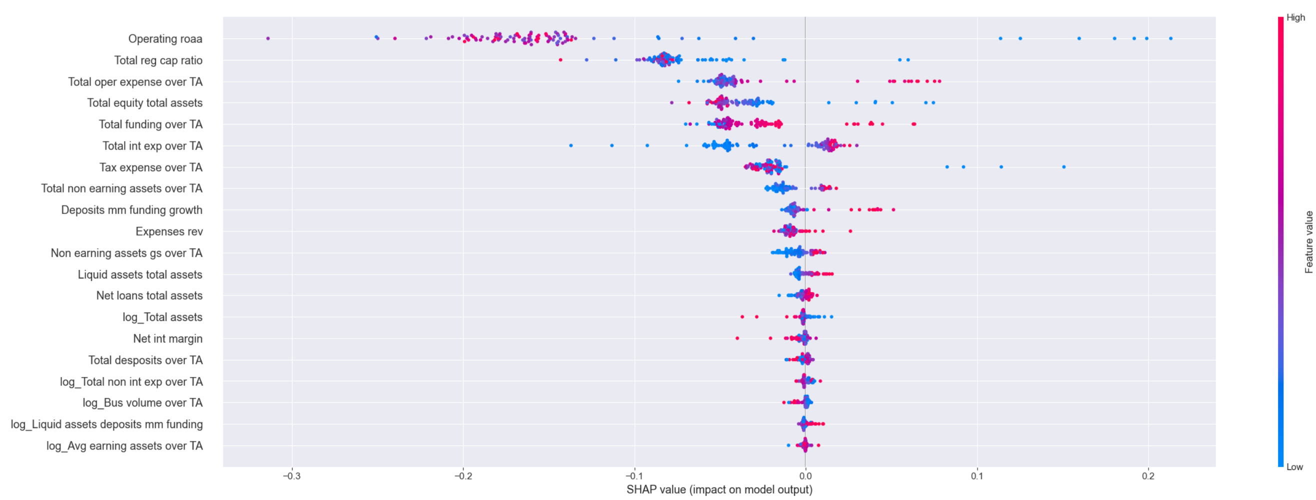
Figure 2: Permutation feature importance (RF)



Source: Authors' calculations.

Shapley values additionally allow to have a look at the nature of the impact of each variable on the probability of default. In line with the CAMELS approach, we notice that variables accounting for capital are associated with a negative impact on the probability of default. In particular, we notice that, for most of their values, TRCR and TE/TA have a negative impact on the probability of default: Shapley values mostly lie on the left of the 0. As for LA/TA, we notice that values associated with a positive impact on the probability of default are the largest values of LA/TA, which is in line with the idea that failed banks panic sell their illiquid assets *prior* to default.

Figure 3: Shapley values (RF)



Source: Authors' calculations.

5.3. Prudential capital ratio's efficiency

Prudential regulation assumes that increasing capital ratios is key to ensuring financial stability. From a microprudential perspective, this implies that capital requirements reduce bank default risk. If such a negative relationship is well-established in the literature, its shape is however not so well-understood. Is it a linear relationship? If this is the case, increasing capital requirements is always efficient from a microprudential perspective. Is it, on the contrary, a non-linear relationship, in which case thresholds could be identified?

Let us start with the results of the logistic regression. Having a look at Table 3, we notice first that the liquidity ratio (LA/TA) has only a small impact on the default probability. Second, both capital ratios (TE/TA and TRCR) have a negative impact on the default probability. In addition, the odd ratio associated with ROAA is significantly smaller than 1, which is consistent with the theory.

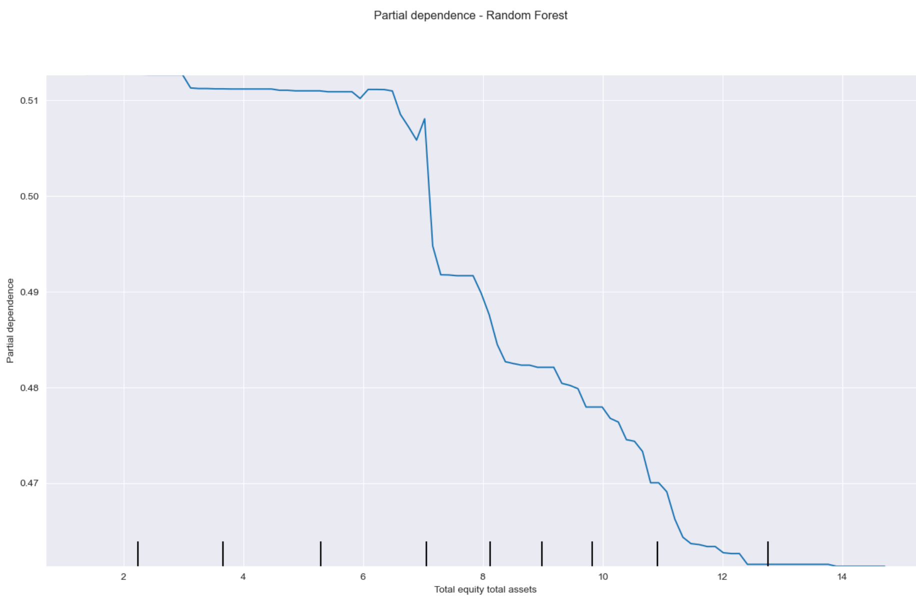
Table 3: Logistic regression results

Variable	Weight	Odds ratio	Std. Error
Const	1.7336***	5.23	0.041
TE/TA	−0.1463***	0.8638	−0.1463
TRCR	−0.1079***	0.8977	−0.1079
LA/TA	0.0515***	1.0529	0.0515
ROAA	−0.8213***	0.4398	−0.8213

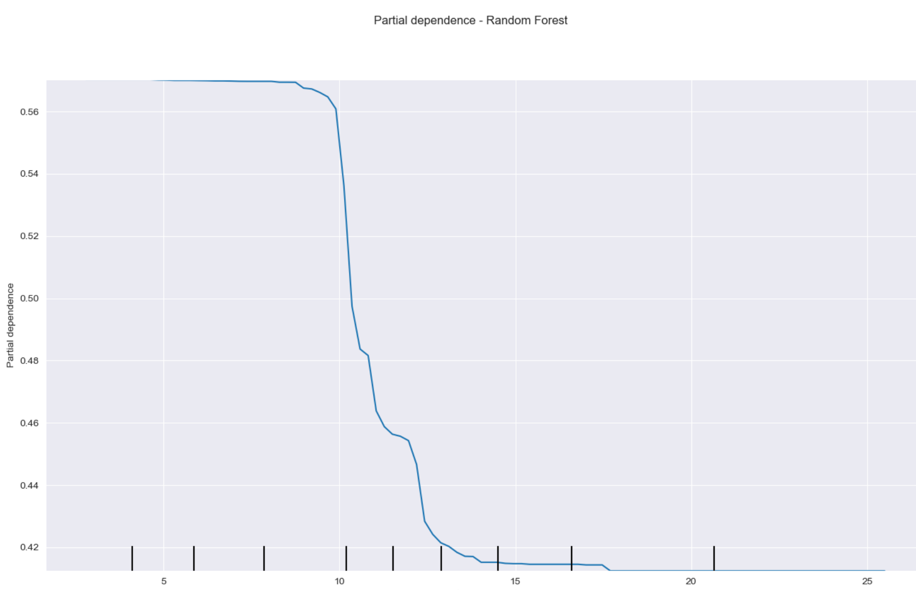
Source: Authors' calculations, with *: p-value < 0.1, **: p-value < 0.05, ***: p-value < 0.01.

Figure 4: Partial Dependence Plots (PDPs) - RF

(a) TE/TA



(b) TRCR



Source: Authors' calculations.

These results are confirmed by the non-linear models as can be seen in Figures 4:[5] solvency ratios have a negative impact on default probability. Moreover, the partial dependence plots suggest that the relationship between capital ratios and the probability of default is non-linear. More precisely, it seems that above some values of the capital ratios, no further impact on the probability of default can be obtained from an increase in capital requirements:

- other things being equal, the default probability sharply decreases when the leverage ratio goes from 7 to 12%, but stabilizes for values of TE/TA above 12%,
- other things being equal, the probability of default is sharply reduced when the risk-weighted ratio goes from 10 to 15%, reaching then its lowest value.

In other words, from a microprudential perspective, it would be efficient to strengthen capital requirements to reach the values of the capital ratios for which the probability of default is at its lowest.

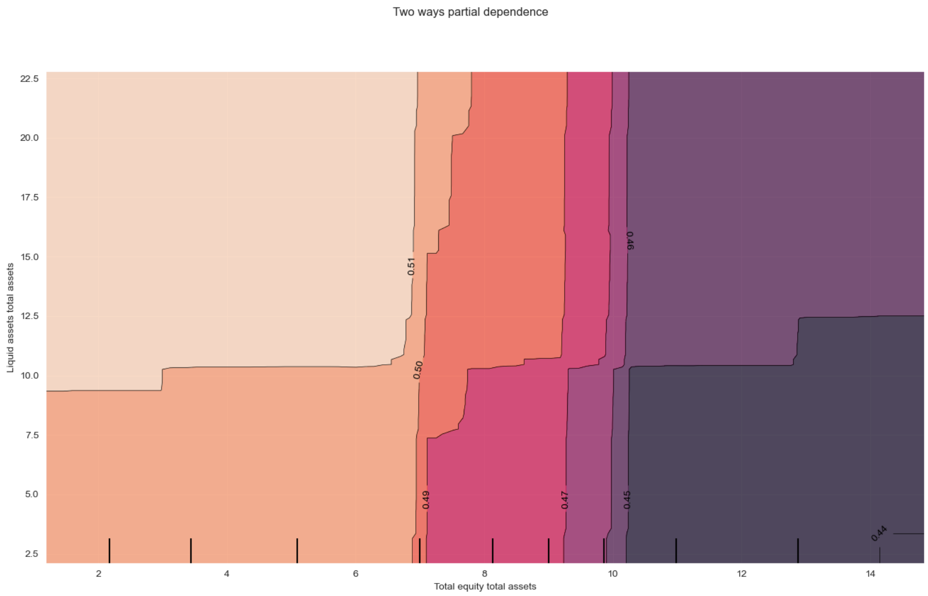
5.4. Interaction between liquidity and solvency risks

Basel III has introduced two liquidity ratios. The purpose of these ratios is to prevent the liquidity spirals observed during the 2007-08 crisis from materializing. If such spirals were indeed witnessed at that time, it is not so clear that they were actually completely unrelated to banks being generally under-capitalized. Indeed, as Pérignon et al. (2018) show it for Europe, no actual market-wide liquidity dry-up occurred between 2008 and 2014 and banks suffering from liquidity dry-ups during this period were often the least-capitalized ones. In this section, we study the interaction between capital and liquidity. In particular, we try to determine which of the two drives the most the probability of default. We have actually already offered a hint in section 5.2. Indeed, Figures 2 and 3 show that capital (both TRCR and TE/TA) is a greater predictor of bank default than liquidity. Let us provide additional evidence to this idea. Figure 5 displays two-way PDPs for RF when TE/TA and LA/TA are considered, while Figure 6 displays two-way PDPs when TRCR and LA/TA are considered. These figures thus provide insight concerning the impact of the interaction between capital variables (TE/TA and TRCR) and the liquidity ratio (LA/TA) on the probability of default.

Having a look at the impact of the interaction between TE/TA and LA/TA on the probability of default (Figure 5), we notice that it seems to be mostly driven by the variable accounting for capital (TE/TA). The same goes for the impact of the interaction between TRCR and LA/TA on the probability of default (Figure 6). Indeed, in both cases, the shape of the surfaces is mostly determined by the value of the variable accounting for capital, while changes in the value of LA/TA impact only marginally the probability of default.

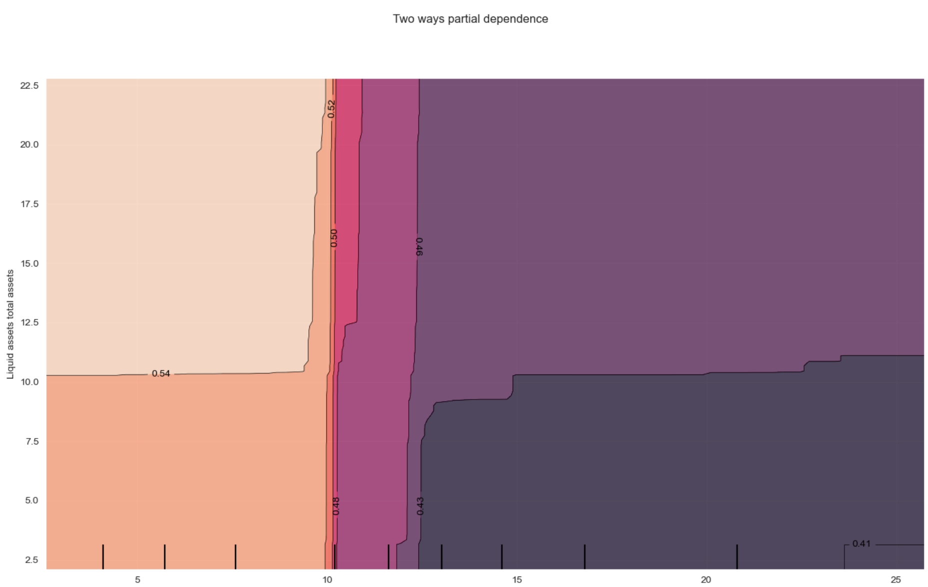
[5] Like in the previous section, we only display random forest's results since it is the model with the highest macro recall in the test sample. Results for the other models are available on the companion website. It should be noted that all results go in line with those of the random forest model.

Figure 5: Two-way Partial Dependence Plots (PDPs) – TE/TA and LA/TA



Source: Authors' calculations.

Figure 6: Two-way Partial Dependence Plots (PDPs) – TRCR and LA/TA



Source: Authors' calculations.

In particular, we notice that it is only when TE/TA $> 10\%$ that the lowest probability of default can be reached (Figure 5). Similarly, when TRCR $< 15\%$, the probability of default is large no matter the value of LA/TA, while when TRCR $> 15\%$, the probability of default is low no matter the value of LA/TA (Figure 6). As a consequence, it seems that liquidity is not *per se* a strong driver of bank default. However those results should be taken with caution: we discuss this point in section **??**.

6. Robustness

For reasons of space optimization we choose to display robustness checks on our companion website. To summarise what is being done in this section:

- we discuss and give statistics on the decision threshold above which models predict ones
- results given by Accumulated Local Effects, an alternative to PDPs that takes into account for potential correlation between variables, are presented
- we summarise our findings given by the models without over-sampling data
- we give comparisons of our results with those obtained when standardizing predictors

7. Conclusion

Banking prudential regulation defines requirements meant to ensure financial stability. To assess the microprudential efficiency of the Basel III standards, we studied the predictive power and the nature of the impact of an increase in the prudential ratios on banks default probability.

What is striking is the lack of consensus in the academic literature concerning both the design of these rules and the potential unintended consequences of their joint-implementation. Moreover, the banking crisis experienced both in the US and in Europe in 2023 suggests that the rules implemented after the 2007-08 crisis may not be up to the task: prudential ratios are efficient but might be set higher. This paper provides evidence that allows to better assess the current state of banking regulation. Implementing various bankruptcy prediction models on a database comprising 4707 US banks and 454 observations of default on the period 2000-2018, we indeed manage to offer new insights on banking regulation.

We provide answers to two key questions for banking regulation: that of capital requirements' efficiency and that of the impact of the interaction between liquidity and capital on the probability of default. We show that capital requirements as defined by Basel III might be increased as it would lower banks' default risk. In addition, according to the evidence provided by Durand and Le Quang (2022), strengthening capital requirements would not hamper banks' activities. Concerning the liquidity ratios, our results suggest that liquidity cannot be considered as a strong predictor of bank default.

Finally, regarding our methodological findings, as expected, logistic regression remains a strong model: it shows high predictive power, gives values for parameters and statistical inference tools. In addition, our results from statistical learning models underline the idea of complementarity between standard approaches and learning methods. Indeed, as shown by random forest results, non-linearities in predictors' interactions and impact can be revealed when relaxing assumptions on the functional form of the model. From this perspective, we eventually recommend the use of random forest and gradient boosting methods to study optimal capital structure and optimal ratios' value since those approaches seem to be efficient in finding turning points.

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