Banking prudential regulation efficiency : the return of the leverage ratio

Pierre Durand

Université Paris Nanterre

200 av. de la République
92001 Nanterre Cedex
www.parisnanterre.fr

Ecole doctorale 396 : Economie, Organisations, Société
Laboratoire : EconomiX (UMR CNRS 7235)

Membre de l'Université Paris Lumières

Pierre Durand

Efficacité de la règlementation prudentielle bancaire

Le retour du ratio de levier

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Jury :

Rapporteur :	Monsieur Vincent Bouvatier	Professeur, Université Paris-Est Créteil
Rapporteur :	Monsieur Christophe Hurlin	Professeur, Université d'Orléans
Membre du jury :	Madame Laëtitia Lepetit	Professeure, Université de Limoges
Directrice de thèse :	Madame Valérie Mignon	Professeure, Université Paris Nanterre
Membre du jury :	Madame Laurence Scialom	Professeure, Université Paris Nanterre

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> "The delicate balance of mentoring someone is not creating them in your own image, but giving them the opportunity to create themselves."
>
> *Steven Spielberg*

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"Tu veux savoir la différence entre le maitre et l'élève ? Le maitre a échoué plus de fois encore que l'élève n'a essayé."

Yoda – L'empire contre attaque, 1980

Je tiens évidemment à remercier grandement les membres de mon jury. Vincent Bouvatier et Christophe Hurlin, merci infiniment d'avoir accepté de rapporter cette thèse. Vincent a mon entière gratitude pour m'avoir proposé de relire mon premier chapitre. Laëtitia Lepetit, un grand merci de m'avoir fait l'honneur de compter parmi les membres de ce jury. Bien entendu, j'adresse mon entière gratitude envers Laurence Scialom pour avoir pris la présidence de ce jury. Merci également pour tes précieux conseils et pour Gaëtan !

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"Pour moi, réaliser un film équivaut à peindre un tableau, à 200 m de la toile avec un talkie-walkie et 80 personnes qui tiennent des pinceaux."

David Fincher

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"C'est copain, c'est son nom. On l'a appelé copain comme cochon."

Monsieur Guilain – Les bronzés font du ski, 1979

Qu'aurait été cette thèse sans les copains ??!! Je recommande à n'importe qui de pouvoir travailler dans une ambiance aussi incroyable que celle du 601. Pendant trois ans, je n'ai pas bossé avec des collègues mais avec de véritables amis et c'est une vraie chance ! Je pense donc très fort à vous Florian et Choubi ! Florian, *mèsi* pour ton soutien et ta force de travail. Tu détestes qu'on en parle, mais ta persévérance et ton mode "machine de guerre" tenu pendant trois ans ont toujours été une source de motivation. Tu as toujours été présent pour donner un coup de main quand j'en avais besoin (je pense notamment à toutes tes relectures !!) et donc pour ça aussi, *a great thank* ! Choubichouxe, ta grande disponibilité en tant qu'ami compte beaucoup ! Ton soutien aura été très important pour moi. En particulier, nos déjeuners (meilleurs croques de Paris) à mi-chemin entre l'ANIA

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> "La Force est puissante dans ta famille. Transmets ce que tu as appris."
>
> *Yoda* – Le retour du jedi, 1983

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À ma mère, mes sœurs, Eloïse et mon père

Table des Matières

[1]See Tables 1.A.1 and 1.A.2 in appendix 1.A for a synthetic presentation.

[2] The results from specification tests are reported in appendix 1.D.

Introduction Générale

A la suite de la crise financière de la fin des années 2000, une refonte importante et profonde de la réglementation prudentielle s'opère. De nombreuses limites et faiblesses du système financier et bancaire sont identifiées et il apparait essentiel de mettre en place un corpus de règles permettant d'y répondre. C'est dans ce contexte que s'inscrit l'élaboration des accords de Bâle III, qui posent les recommandations en termes de politiques prudentielles à l'ensemble des pays membres du Comité de Bâle (*Basel Committee on Banking Supervision*, BCBS). Un nombre important d'exigences réglementaires est alors mis en place dans les principales juridictions internationales. Cyclicité, quand tu nous tiens ! Douze ans plus tard et alors même que l'application des règles préconisées par ces accords n'est pas encore arrivée à terme, une première occasion de tester, en pratique, l'efficacité du nouveau cadre prudentiel se présente : la crise du Covid 19. Au moment où certains pays sortent à peine de leur période de confinement et où une incertitude plane quant à une recrudescence du virus, l'inéluctable impact économique de la crise sanitaire est encore difficile à évaluer. L'ensemble des acteurs de la sphère économique propose déjà un certain nombre d'évaluations des conséquences de la crise et de prospections de ses impacts sur l'ensemble très large des secteurs qui risquent d'être touchés[3]. Les régulateurs ne se seront pas fait attendre et mettent en place un assouplissement de certaines exigences réglementaires, notamment en capital et liquidité[4]. Même si la réactivité des instances de régulation envoie un signal plutôt positif, nous sommes en droit de nous poser la question : si le cadre réglementaire posé après la crise de 2007-09 doit permettre de solidifier le système financier et bancaire mondial, pourquoi l'assouplir à la première résurgence d'une crise ? La réglementation aura-t-elle été suffisante pour permettre au système bancaire d'être résilient face à la crise du Covid 19 ? De manière générale, **la réglementation bancaire a-t-elle un caractère assez intertemporel pour que le système bancaire puisse se remettre efficacement et rapidement de nouvelles éventuelles crises économiques ? C'est cet aspect d'efficacité que nous cherchons à questionner dans cette thèse.** Sans pouvoir assurer que les accords de Bâle III permettront, ou non, de prévenir les prochaines grandes perturbations économiques, nous proposons une approche pour en évaluer l'efficacité. Pour mieux comprendre notre approche et les différents angles que nous adoptons, nous revenons dans un premier temps sur la philosophie dans laquelle s'insère la réglementation bâloise et les raisons qui ont poussé les régulateurs à mettre en place les exigences qui prévalent aujourd'hui. De cette définition de notre cadre de travail, nous déduisons quelques enjeux et limites liés à la réglementation. Ces précisions nous permettent d'exposer le

[3] Parmi d'autres études, nous pouvons citer les 35 bulletins publiés par la Banque des Règlements Internationaux.

[4] Voir, par exemple, le communiqué de presse du Parlement Européen du 19 juin 2020 sur l'assouplissement des règles en Europe pour faciliter le prêt bancaire.

plan de notre thèse et la problématique à laquelle il répond : **sur les plans macro- et microéconomiques, la réglementation prudentielle se révèle-t-elle efficace et sans dommage collatéral pour l'industrie bancaire ?**

0.1 Philosophie et définition de la réglementation

0.1.1 Principes généraux de la (nouvelle) réglementation prudentielle

Brossard et Cheitoui (2003), dans une analyse historique de la réglementation antérieure à 1945, soulignent que "la maturation de la réglementation prudentielle dépend de la façon dont les acteurs de la finance assimilent les leçons de la crise financière". C'était vrai pour la mise en place des exigences prudentielles nationales d'avant guerre, et ça l'est encore pour les trois accords internationaux établis à Bâle respectivement en 1988, 2004 et 2010.

C'est donc après une tendance importante à la déréglementation à l'issue des "30 Glorieuses" et après les perturbations des années 1970 qu'est d'abord créé le Comité de Bâle en 1974, avec pour objectif d'assurer la stabilité d'un système bancaire de plus en plus internationalisé (Goodhart, 2011), puis que les recommandations de Bâle I sont formulées, en 1988. Ces accords incitent les différentes juridictions à mettre en place un ratio de solvabilité minimum : le ratio Cooke, qui établit à 8% du total des actifs pondérés par les risques de crédit, le montant des fonds propres que les banques doivent détenir constamment[5].

C'est également après une crise, celle liée à la bulle internet du début des années

[5] Voir le texte original du Comité de Bâle : "International convergence of capital measurement and capital standards"

2000, que sont constatées certaines des faiblesses inhérentes à la réglementation en vigueur : la structure comptable du ratio de Cooke est trop axée sur le montant des crédits. Autrement dit, seul le risque de crédit est pris en compte. Or, les années 1990 voient les instruments financiers se diversifier, se complexifier et se sophistiquer, ce qui accentue les risques de marché et opérationnel, parallèlement à l'intensification de l'intrication des institutions financières au niveau international. Les accords de Bâle II[6] viennent formuler de nouvelles recommandations : la définition des actifs pondérés par les risques est revisitée et prend en compte les risques de marché et opérationnel, un volet de surveillance prudentielle est mis en place, et l'idée d'une discipline de marché est intégrée *via* la mise à disposition publique des informations sur l'actif et la gestion des risques.

Cette structuration du cadre réglementaire en trois piliers est conservée lorsque, après la "Grande Récession" de 2007-09, le BCBS révise ses recommandations en termes de politique prudentielle pour donner lieu en 2010 aux accord de Bâle III[7]. De la même manière que pour les précédentes révisions du règlement prudentiel, pour comprendre la philosophie dans laquelle se place l'élaboration des derniers accords bâlois, il faut saisir les causes identifiées de la crise bancaire intervenue à la fin des années 2000. Bignon *et al.* (2018) dégagent trois principales causes de la crise qui sont aussi à l'origine des remaniements prudentiels : (i) la fragilité des institutions financières, (ii) le risque de contagion et (iii) l'opacité des transactions. Devant ce constat, pour prévenir le plus de risques possible et dans

[6] Voir le texte original du Comité de Bâle : "Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version"

[7] Voir le texte original du Comité de Bâle : "Basel III: international regulatory framework for banks"

un souci d'exhaustivité, le nombre de ratios réglementaires a été démultiplié et leur composition (notamment celle du ratio de capital) s'est densément précisée[8] : la réglementation en capital a été réévaluée et redéfinie pour intégrer les risques de systémicité et de défaut, un ratio de levier est instauré, et deux ratios de liquidité sont introduits. Par ailleurs, des instruments de résolution interne ont été définis. Bâle III vise également à encadrer les pratiques de management, la systémicité des banques ou encore la discipline de marché. Au delà d'une évidente complexification du règlement prudentiel, discutée en Section 0.2.2, deux points nous paraissent importants dans la compréhension de la nouvelle réglementation. D'une part, les préoccupations macroprudentielles y prennent une place prépondérante et, d'autre part, cette nouvelle règlementation est axée autour de l'idée de "un risque, une règle". Le premier point nous aidera à aborder l'évaluation de l'efficacité du cadre prudentiel actuel, et le second à façonner les recommandations en termes de politiques publiques que nous en déduisons.

0.1.2 Les différents objectifs de la réglementation

Afin de pouvoir mener une évaluation de l'efficacité de la réglementation, il est important d'en comprendre les objectifs. Si ces derniers sont remplis, on peut en déduire que la contrainte réglementaire fonctionne. Comme définie par la Banque Centrale Européenne, la régulation prudentielle bancaire est conçue pour accroitre la résilience des institutions de crédit et supporter la stabilité du système financier

[8] Le détail de la réglementation de Bâle III est donné en Section 0.1.3

dans son ensemble[9]. Il s'agit d'un objectif clairement identifiable et simplement formulé. Déterminer s'il est atteint est autrement plus compliqué.

Les définitions et mesures de résilience et de stabilité financière sont en effet loin d'être triviales. Cette problématique fait l'objet d'une discussion dans la Section 1.3.1 "Financial stability: survey and methodology for a composite indicator" de notre premier chapitre. Nous y dressons notamment le constat que la plupart des études réalisées par les instances de régulation sur la stabilité financière visent généralement un ou plusieurs secteurs clefs de la stabilité financière[10]. Il n'existe pas en revanche de mesure consensuelle de stabilité financière globale. Les préoccupations macroprudentielles sont pourtant prépondérantes dans la conception des accords de Bâle III[11] (Bennani *et al.*, 2017). Afin d'évaluer l'efficacité des règles prudentielles, il nous parait donc primordial de nous confronter à cette question de la mesure de la stabilité financière et des impacts des règles bâloises sur elle.

Ainsi que nous le développons ci-après, les exigences réglementaires prennent avant-tout la forme de contraintes bilancielles adressées aux banques individuellement. Leur construction est donc principalement microprudentielle. De ce point de vue, l'objectif de la réglementation est, entre autres, de réduire le risque de défaut des banques.

Enfin, la régulation doit pouvoir s'appliquer sans contraindre l'activité des

[9] Maddaloni et Scopelliti (2019) : "Banking regulation and supervision are designed to increase the resilience of credit institutions and to support the stability of the financial system overall."

[10] C'est notamment le cas des rapports de stabilité financière (GFSR) proposés bi-annuellement par le Fond Monétaire International (FMI).

[11] Voir la Section 0.1.3 pour plus de détails.

institutions. Brossard et Chetioui (2003) établissent d'ailleurs que la structure concurrentielle de l'industrie bancaire est un déterminant de l'efficacité prudentielle. Par ailleurs, la Banque Mondiale souligne l'importance de la compétitivité au sein du secteur bancaire dans la détermination de la stabilité financière (Allen *et al.*, 2009) : la perte de pouvoir de marché pourrait entrainer une fragilisation de la capacité des banques à générer du profit et, en conséquence, à prendre des risques. Si la réglementation contraint trop fortement les banques, un effet non-attendu pourrait être l'augmentation de la prise de risque et la fragilisation du secteur. Les effets de la réglementation sur le profit des banques, sont donc à prendre en compte lorsque l'on s'intéresse à l'efficacité de la réglementation.

0.1.3 Bâle III

Nous précisons brièvement ici la structure de la réglementation telle que recommandée par Bâle III. Nous nous arrêtons principalement sur les aspects de la réglementation qui nous intéressent pour cette thèse.

Comme évoqué ci-avant, les accords de régulation prudentielle bancaire de 2010 conservent la structuration en trois piliers, mise en place sous Bâle II :

- *Pilier 1* : ce pilier définit les exigences en capital[12].
  - Le ratio de solvabilité, ou de capital, a pour objectif de renforcer la capacité d'absorption des pertes des banques. Bâle III préconise que le niveau des actions ordinaires (CET1) doit représenter 4,5% du montant

[12] Puisque non traité dans cette thèse, nous n'évoquons pas ici certaines composantes de ce pilier : le traitement de la titrisation, la gestion du risque de contrepartie, ou encore l'exposition des banques aux chambres de compensation. Sur ces derniers points, on pourra consulter la BIS : *The Basel Framework*

des actifs pondérés par les risques (RWA). S'ajoute à ce seuil, un coussin de conservation à hauteur de 2,5%[13]. Le niveau minimum de capital dur est donc établi à 7% des RWA. En prenant en compte les contraintes en capital Tier 1 et 2, on obtient un seuil minimum pour le ratio de capital à 10,5% des RWA. Il faut ajouter à cela, un volant contra-cyclique pouvant varier de 0 à 2,5% des RWA en fonction du cycle. Enfin, une surcharge systémique est instaurée et peut varier de 0 à 3,5% des actifs pondérés par les risques. Au total et en fonction du cycle et du niveau de systémicité d'une banque, le ratio de capital requis peut varier de 10,5 à 16,5%.

  – Bâle III introduit également un ratio de levier à hauteur de 3% : les fonds propres doivent représenter au moins 3% du bilan et hors bilan de la banque. Son objectif est de limiter un excès de financement par la dette. Ce ratio, bien plus simplement défini, permet en outre de diminuer la prise de risque (Bignon *et al.*, 2018) et d'être moins sujet aux modèles internes.

- *Pilier 2* : ce pilier encadre la procédure de surveillance de gestion des fonds propres et de prise de risque par le régulateur. Il veille donc à ce que les banques disposent des capitaux suffisants pour supporter les risques qu'elles endossent, et aient recours à des pratiques de gestion des risques saines. En outre, ce pilier concerne également les prises de risques liées aux expositions

[13]Ce montant peut varier, notamment en période de crise, mais sous risque de se voir imposer des restrictions en termes de distribution de dividendes.

hors-bilan et de titrisation.

- *Pilier 3* : ce dernier pilier concerne les règles de publication des composantes des ratios réglementaires. Le pilier 3 encadre donc les contraintes en termes de discipline de marché.

Bâle III introduit également deux nouveaux ratios portant sur la liquidité. Le *Liquidity Coverage Ratio* (LCR) et le *Net Stable Funding Ratio* (NSFR).

- Le LCR, rapportant le montant des actifs hautement liquides (*High Quality Liquid Assets*, HQLA) au total des sorties de liquidité dans une période théorique de trente jours de crise de liquidité. L'objectif ici est de renforcer la capacité des banques à respecter leurs engagements en cas de crise de liquidité.

- Le NSFR établit que le montant des financements stables doit être supérieur au montant des financements nécessaires. Ce ratio est dit de long-terme et doit assurer la stabilité du financement des banques.

L'introduction de considérations macroprudentielles dans les accords de Bâle III passe donc par le coussin contra-cyclique et le coussin de systémicité, qui composent tous deux le ratio de capital. L'exigence en capital contra-cyclique varie en fonction du niveau de risque de bulle de crédit évalué par le régulateur. Comme précisé plus avant, il peut varier de 0 à 2,5% des actifs pondérés par les risques.

Le coussin systémique constitue une surcharge en capital pour les banques identifiées comme portant un risque pour l'ensemble du système en cas de défaut.

L'objectif de cette règle est, entre autres, de limiter le paradigme du "Too Big To Fail". Le Bureau de Stabilité Financière (FSB), sur la base de cinq critères[14], attribue une mesure de systémicité aux banques les plus importantes. En fonction de ce score (*Global Systemically Important Banks Score*) les banques les plus systémiques peuvent se voir attribuer une surcharge en capital.

Enfin, deux normes de résolution sont mises en place pour pallier la nécessité d'une intervention des pouvoirs publics en cas de perturbations : le *Total Loss Absorbing Capacity* (TLAC) et le *Minimum Requirement for own funds and Eligible Liabilities* (MREL).

0.2 Enjeux et limites

0.2.1 Spécificité et temporalité

Dans son discours sur les outils de politique macroprudentielle le 13 août 2014, Claude Borio, chef du département monétaire et économique à la Banque des Règlements Internationaux (*Bank of International Settelments*, BIS), évoque les lacunes des *stress tests* :

> "As early warning devices to identify vulnerabilities in tranquil times, they have so far proved woefully deficient. Their effectiveness is undermined by limitations of the modelling technology, not least the ability to capture sudden changes in behaviour, and by the context, not least the "this-time-is-different" syndrome. No macro stress test, in fact, identified

[14] La taille, le degré d'interconnexion avec d'autres institutions financières, leur degré de substituabililité, le niveau de leurs activités transfrontalières et leur niveau de complexité.

> the serious vulnerabilities that ushered in the financial crisis. While improvements have been made, there is a risk of putting too much faith in the tool's remedial properties."

Cette critique est applicable à l'ensemble des mesures réglementaires : au delà des contraintes en termes de modélisation technique, l'évaluation de l'efficacité des règles prudentielles se heurte à la difficulté qu'il y a de prendre en compte les changements de comportements, la mutation des risques et l'excès de confiance dans l'idée que la règle établie est la bonne[15].

La réglementation post-crise est spécifique à la crise : des risques sont identifiés, et des règles sont mises en place pour les pallier. Si tant est que toutes les faiblesses nous conduisant au marasme de la fin des années 2000 aient été repérées et traitées, une limite de cette démarche tient de à que les risques mutent (White, 2014). Ainsi, il n'est pas impossible que la réglementation définie par Bâle III soit inadaptée aux faiblesses du système bancaire des prochaines décennies. Pour reprendre l'exemple précédemment cité, les conséquences économiques et financières de la crise sanitaire de 2020 seront le terrain d'une évaluation, en pratique, de la pertinence du cadre réglementaire : si les répercutions de cette crise sur le secteur bancaire sont fondamentalement différentes de celles engendrées par l'euphorie puis la crise financière des années 2000, il y a fort à parier que la réglementation en vigueur ne sera pas en mesure d'assurer une résilience forte du système.

Nous soulignons ici la possibilité que Bâle III définisse un cadre prudentiel dont

[15]Sans parler d'excès de dette publique, nous faisons ici référence au syndrome "cette fois c'est différent" (Reinhart et Rogoff, 2009) qui décrit la croyance générale dans l'idée que les crises appartiennent au passé.

l'efficacité pourrait s'avérer éphémère. La réglementation nécessite soit de pouvoir s'adapter constamment, risquant ainsi que les ajustements se fassent *a posteriori* des crises[16], soit de proposer des règles dont l'efficacité est intertemporelle, c'est à dire, non spécifique aux risques identifiés d'une période.

Nous proposons dans cette thèse de répondre à cet enjeu, en n'évaluant pas l'atteinte des objectifs de chacune des règles, mais en nous intéressant à une dimension plus large de la réglementation : renforcer la stabilité financière (Chapitre 1) et diminuer le risque de faillite bancaire (Chapitre 2).

0.2.2 Répondre à la complexité par la complexité

Face à un système bancaire marqué par une complexité caractéristique à la fois des produits financiers et de la structure des banques qui le composent, les instances régulatrices répondent par... la complexité (Bignon *et al.*, 2018). Nous pouvons définir cette complexité réglementaire à deux niveaux.

Premièrement, nous avons à faire à un corpus de règles très fourni : les accords de Bâle III sont complexes par le nombre d'exigences réglementaires qu'ils définissent[17]. Le coût d'entrée pour comprendre le fonctionnement de la réglementation définie et recommandée par Bâle III est donc élevé. Ce niveau de complexité induit un manque de transparence dans le lien entre les règles et l'objectif de stabilité

[16] Cela a été le cas des trois accords de Bâle.

[17] Il faut ajouter à cela, le fait que ces accords constituent des recommandations. Par conséquent, la complexité de la réglementation prudentielle actuelle tient aussi des différences dans la transposition de ces accords au sein des différentes juridictions : le RCAP (*Regulatoy Consistency Assessment Programme*) réalisé par la BIS, couvre 28 juridictions. Certaines d'entre elles, comme l'Europe, comptent plusieurs pays, dans lesquels les régulateurs nationaux gèrent localement la mise en place de certaines règles. Ainsi, à titre d'exemple, les règlements et directives européens CRR/CRD-IV, assurent la transposition des accords de Bâle III au niveau de l'Europe, offrant donc certaines différences avec la transposition de ces mêmes accords dans d'autres juridictions telles que la méthode de pondération des actifs par les risques, le calcul du score de systémicité des banques, etc. A un deuxième niveau, l'application du contrôle prudentiel en Europe revient en partie (pour ce qui concerne le Pilier 3 notamment) à la charge des régulateurs nationaux.

financière et dans l'appréhension des interactions potentielles entre les règles[18].

Par ailleurs, la réglementation est complexe en tant que telle, c'est à dire qu'elle établit des règles qui sont complexes dans leur définition. C'est le cas du ratio de liquidité de court-terme : le LCR. En effet, le calcul du dénominateur (les sorties nettes de liquidité dans une période de 30 jours de crise de liquidité) de ce ratio est difficilement reproductible à partir de données publiques, et la définition de son numérateur (les actifs liquides de haute qualité) est source de débats. C'est aussi le cas du ratio de solvabilité. En effet, la construction des actifs pondérés par les risques est tout à la fois dépendante du cycle (Bignon *et al.*, 2018) et définie de manière assez floue pour que les banques les plus importantes puissent agir dessus pour réduire leur contrainte en capital (Carpenter et Moss, 2013). La compréhension des règles est complexe, leur calcul également et donc leur *reporting* aussi.

Ainsi, la complexité réglementaire génère un double problème d'opacité : le manque de visibilité globale des règles rend peu compréhensible l'information sur leur efficacité, un enjeu pourtant d'ordre public puisqu'elles doivent assurer la stabilité du système financier ; et une opacité qui rend nécessairement plus ardue la tâche du régulateur[19].

[18]La Banque d'Angleterre souligne aussi la complexité lexicale du corpus réglementaire (Amadxarif *et al.*, 2019).

[19]De ce point de vue, la complexité prudentielle favorise l'étroitesse des liens entre les instances de régulation publiques et l'industrie bancaire. Au delà du questionnement démocratique que cela pose, l'efficacité réglementaire s'en voit détériorée (Bignon *et al.*, 2018; Veltrop et Haan, 2014; Mishra et Reshef, 2018)

0.2.3 "Dommages collatéraux" potentiels

Nous avons abordé jusque-là l'efficacité de la réglementation en exposant son objectif de renforcement de la stabilité financière et comment les règles établies sous Bâle III sont supposées le remplir. Cependant, il ne faut pas que les exigences prudentielles se posent en contrainte au bon fonctionnement du secteur : les banques doivent pouvoir assurer leur rôle de création de liquidité et de transformation des risques. Nous abordons ici un argument souvent avancé par l'industrie bancaire, selon lequel la réglementation contraint les banques dans leur capacité à générer du profit, augmente leur coût de financement et détériore finalement leur rôle créditeur.

Un certain nombre d'études souligne le rôle de la rentabilité des banques dans la stabilité financière (Keeley, 1990; Xu *et al.*, 2019), et d'autres mettent en évidence une relation négative entre réglementation en capital trop forte et rentabilité (Goddard *et al.*, 2013; Baker, 2013). De ce point de vue, le renforcement des exigences bâloises de 2010 vient fragiliser le système bancaire et la stabilité financière.

Toutefois, ce point de vue est loin de faire consensus au sein de la littérature économique. En effet, plusieurs travaux montrent qu'une meilleure capitalisation des banques entraine une diminution du risque lié à leur activité et donc de leur coût de financement (Admati *et al.*, 2013; Gambacorta et Shin, 2018). Ainsi, plusieurs auteurs soutiennent qu'une relation positive peut être établie entre certaines règles prudentielles et la rentabilité bancaire (Berger, 1995; Berger et Bouwman, 2009;

Iannotta *et al.*, 2007; Lee et Hsieh, 2013).

Le travail de recensement d'études réalisé par la BIS[20] souligne cette absence de consensus :

- Sur 25 études portant sur l'impact du ratio de capital sur l'activité de prêt des banques, 12 identifient un impact négatif, 13 un effet positif.
- Sur 18 études analysant l'effet du ratio de levier sur l'activité de prêt des banques, 5 obtiennent un impact négatif et 13 un impact positif.
- L'effet du LCR sur l'activité de prêt est estimé négatif 13 fois sur 18.
- 55 études portant sur les effets du ratio de capital sur les coûts de financement des banques sont recensées. 32 obtiennent un impact positif et 23 un impact négatif. La même répartition est obtenue concernant l'effet du ratio de levier.
- 34 papiers trouvent un effet positif du LCR sur le coût de financement et seulement 2 un impact négatif.
- La littérature est en revanche plus consensuelle quant à l'impact des ratios de capital, de levier et de liquidité sur le taux de prêt : l'effet est positif.

Dans un contexte où le secteur bancaire est mis en concurrence avec des modes de financement alternatifs, non-intermédiés et souvent moins régulés[21], la fragilisation du secteur bancaire par la réglementation pourrait amoindrir ses effets sur la stabilité financière. Par conséquent, il nous semble pertinent de déterminer l'impact individuel et cumulé des différentes exigences réglementaires

[20]Voir le projet *Financial Regulation Assessment: Meta Exercise* (FRAME) réalisé par la BIS.
[21]Nous faisons ici référence au *shadow banking*.

sur la rentabilité des banques, le niveau des crédits qu'elles accordent, ou encore le niveau des taux de ces crédits dans l'analyse de l'efficacité du règlement prudentiel.

0.3 Proposition d'une réponse

Cette thèse a pour objectif d'évaluer l'efficacité de la réglementation sous certains des différents angles évoqués précédemment. Plus précisément, nous évaluons l'efficacité de la réglementation sur les plans macroéconomique et microéconomique. Ce dernier est traité de deux points de vue différents : celui de l'objectif de renforcement de la solidité du secteur bancaire et celui des répercussions non désirées potentielles de la réglementation sur l'industrie bancaire.

L'une des ambitions de cette thèse, au delà de l'évaluation de l'efficacité de la réglementation prudentielle bancaire actuelle, est aussi de **proposer des réponses aux enjeux et limites de ces exigences réglementaires**. Plus précisément, nous proposons que la réglementation soit axée sur un ratio de levier plus mordant : cela permettrait à la fois de répondre à la nécessité d'une règle intertemporelle, moins complexe et non-contraignante pour le bon fonctionnement du secteur bancaire.

Le premier chapitre de cette thèse s'intéresse à l'efficacité de la réglementation prudentielle d'un point de vue macroéconomique et répond à la question : les exigences bâloises en capital et liquidité permettent-elles de renforcer la stabilité financière ? La réponse à cette interrogation se heurte dans un premier temps à la définition et la mesure de la stabilité financière. Le FMI propose une batterie d'indices de solidité financière[22]. De façon redondante, nous pouvons trouver parmi ces indicateurs, les montants de ratios prudentiels définis par Bâle III, agrégés aux niveaux national et régional : nous nous retrouvons donc à mesurer la stabilité financière par les ratios prudentiels, eux-mêmes construits sur l'hypothèse qu'ils renforcent la stabilité financière. Devant l'inexistence d'une mesure robuste et communément acceptée de stabilité financière, nous proposons dans un premier temps une méthode de calcul pour un tel indicateur fondé sur une analyse en composantes principales à partir de variables macroéconomiques. Dans un second temps, nous estimons l'impact individuel et combiné des ratios de capital et de liquidité sur cet indicateur. Pour ce faire, nous avons recours à l'estimation d'un modèle non-linéaire à transition lisse en panel (*Panel Smooth Transition Regression*, PSTR) sur des données comptables de 1600 banques agrégées au niveau de 23 pays et sur la période 2005-2016. Les estimations que nous menons différencient les banques en fonction de leur niveau de systémicité, nous permettant ainsi de prendre en compte l'un des aspects macruprudentiels de Bâle III. Nos résultats montrent que les ratios de capital et de liquidité ont un impact positif sur la stabilité financière pour de faibles valeurs. Lorsque ces ratios croissent, leur effet devient moins perceptible. Au delà des résultats de nos estimations, nous soutenons dans ce chapitre que pour pouvoir mener une politique macroprudentielle efficace et l'évaluer, il est nécessaire que le sujet de la mesure de la stabilité financière soit

[22] Voir *Financial Soundness Indicators* mis à disposition par le FMI.

investi plus largement.

Dans le deuxième chapitre, nous abordons la question de l'efficacité réglementaire d'un point de vue microéconomique. L'objectif de ce chapitre est d'évaluer l'effet des ratios de capital, de levier et de liquidité sur la probabilité de défaut des banques. La littérature aborde ce sujet de deux manières : *via* l'utilisation de mesures représentatives de la distance au défaut telles que le Z-score, et l'analyse d'observations de faillites bancaires. C'est la deuxième approche que nous adoptons. En effet, nous procédons à l'évaluation du pouvoir prédictif et de l'impact sur le défaut des banques d'un large panel de variables bilancielles bancaires. Pour cela, nous avons recours à trois modèles de classification : la régression logistique, les forêts aléatoires et les réseaux de neurones. Nous menons cette analyse sur un échantillon de 4707 banques américaines dont 454 défauts, et 3529 banques européennes dont 205 défauts, sur la période 2000-2018. Dans le cas des banques américaines, nos résultats soulignent une relation négative entre les ratios de capital et de levier sur la probabilité de défaut. L'effet de la liquidité ressort positif, ce que nous expliquons par la période de bas taux d'intérêt dans laquelle notre étude s'insère. Les résultats concernant les banques européennes sont plus délicats à interpréter, ce qui est dû à l'absence d'une liste publique et officielle des banques européennes ayant fait défaut. Dans l'ensemble, nos résultats nous conduisent à soutenir la mise en place d'un ratio de levier plus fort, au détriment d'un ratio de solvabilité moins important. En effet, ces deux ratios apparaissent aussi déterminants l'un que l'autre dans la probabilité de défaut. En revanche, le caractère intemporel et simple du ratio de levier lui donne un avantage certain pour répondre aux enjeux mis en évidence plus avant. Ces résultats sont corroborés par notre dernier chapitre.

Le troisième chapitre porte une analyse des déterminants de la rentabilité bancaire. Nous cherchons ici à évaluer l'efficacité de la réglementation prudentielle sur un plan microéconomique, au regard de ses répercussions éventuelles sur le bon fonctionnement de l'industrie bancaire. Nous cherchons également à évaluer l'effet combiné des ratios prudentiels sur la rentabilité bancaire. De la même manière que pour le chapitre précédent, nous avons recours à un large échantillon de variables bilancielles. Nous scindons notre bases de données en deux : l'une contient le LCR et couvre la période 2012-2018 pour un peu plus de 300 banques, et l'autre sans le LCR[23] de 2000 à 2018 pour plus de 1100 banques. Afin de renforcer la qualité de nos résultats, nous faisons également appel à plusieurs mesures de rentabilité. En outre, nous comparons les effets des ratios prudentiels sur la rentabilité mesurée par le rendement des actifs moyens (*Return On Average Assets*, ROAA) et par le rendement des capitaux propres moyens (*Return On Average Equity*, ROAE). Deux modèles sont utilisés pour mener nos estimations : le modèle Lasso et les forêts aléatoires. Nos résultats montrent que le ratio de levier a un impact positif sur la rentabilité mesurée par le ROAA. En revanche, l'impact de ce même ratio sur la valeur actionnariale, mesurée par le ROAE, est généralement faible mais négatif. Néanmoins, nous obtenons que ce ratio prédomine les ratios de capital et de liquidité dans la détermination de la rentabilité[24]. Nous déduisons de ces

[23]Le LCR est mis en place récemment et encore peu de données sont disponibles.
[24]D'une part, nous obtenons que l'importance prédictive de ce ratio est supérieure à celle des deux autres.

résultats qu'un ratio de levier fort ne contraint pas les performances de l'activité bancaire mais celles de la valeur actionnariale. Si ces résultats peuvent expliquer la virulence de l'industrie bancaire à s'opposer à de fortes contraintes en levier, ils viennent certainement confirmer l'idée selon laquelle un ratio de levier pourrait constituer une piste d'amélioration de la réglementation pour qu'elle réponde aux enjeux explicités précédemment.

D'autre part, quand nous étudions l'impact cumulé du ratio de levier avec le ratio de capital ou de liquidité, il apparait que l'effet du ratio de levier outrepasse celui des deux autres.

Chapitre 1

On the impact of capital and liquidity ratios on financial stability[†]

[†]Une première version de ce chapitre a été publiée en tant que Document de travail : Durand P. (2019), "On the impact of capital and liquidity ratios on financial stability", Working Paper EconomiX 2019-4. Je suis particulièrement reconnaissant envers Valérie Mignon pour ses conseils et remarques. Je remercie également Christophe Boucher et Sandrine Lecarpentier pour leurs commentaires et suggestions.

1.1 Introduction

Over the past 30 years there have been 30 banking crises in Basel Committee-member countries, corresponding to a 5% probability of a Basel-Committee member facing a crisis in any given year (S. Walter, *Basel III, Stronger banks and more resilient financial system*, BIS speech conference, April 6th 2011). In the aftermath of the recent financial crisis, G20 felt the urgent need to ask the Basel Committee to reassess prudential banking regulation. Finding a solution to ensure financial stability became a priority for international leaders and regulators. It is in this context that Basel III agreements were born. The overall idea of this reform is to ensure financial stability by improving the banking system resiliency, decreasing systemic risk and contagion effects, and preventing spillovers from the financial sphere to the real one (BCBS, 2010). This chapter falls within this context by proposing an in-depth analysis of financial stability based on prudential ratios.

Several important changes have been made since the first two sets of agreements in order to reach this goal. To capture those developments, let us briefly look back at what happened before 2007 in terms of regulation. After a period of troubles in the 1970s and the deregulation trend of the 1980s, a wish for a more stable and resilient financial system emerged. That is when, in June 1988, the Basel Capital Accord (Basel I) took place, mandated by the G10 in the perspective of limiting credit risks. The flagship ratio of this series of agreements is the Cooke ratio designed for solvency purposes.[1] But an important issue with this ratio is its accounting methodology for credit amount, as it neglects borrowers' quality. That is why, after the internet bubble of the early 2000s, the Basel Committee came with new regulatory recommendations in 2004, namely Basel II. The capital adequacy framework is reassessed under three pillars.[2]

The 2007-2008 financial crisis once again questioned the ability of regulatory requirements to ensure financial stability and a new set of regulation recommendations has been proposed in December 2010. Basel III agreements are based on four main points: (i) the need for financial institutions' reinforcement by setting new standards (equity, liquidity, risk management and compensation policies); (ii) struggling against the "too big to fail" paradigm identifying systemic institutions, imposing them more important absorption capacity requirements and establishing recovery and resolution plans; (iii) making over the counter derivatives market safer; (iv) and making the shadow banking finance sector healthier and safer. This reform keeps Basel II's functioning system articulated around three pillars, adding a macroprudential component. Specifically, equity requirements are organized on three pillars.[3] Besides those equity requirements, Basel III agreements define two

[1]It stipulates that banks with an international presence are required to hold capital equal to 8% of their risk-weighted assets.

[2]The first one reviews equity requirements resulting in the McDonough ratio. The second one establishes a prudential surveillance. The third one sets the market discipline by enforcing disclosure and transparency rules. Considerations on trading book were added in 2006.

[3]Pillar 1 contains equity requirements setting new solvency ratios. The Common Equity Tier 1 (CET1) ratio (4.5%), the Tier 1 ratio (6%) and the Total Capital ratio (8%), weighted by assets' risks. A conservation buffer is fixed to 2.5% of CET1. A countercyclical buffer is added for systemic banks (between 0 and 2.5% of CET1 depending on the level of systemicity of the bank). A leverage ratio is also added (not risk weighted) in order to prevent from excessive leveraged banks. The two macroprudential buffers are the conservation and the Global Systemically Important Banks (GSIBs) buffers. Pillar 2 includes individual requirements for prudential surveillance and risk management purposes. It takes into account securitization and off-balance sheet activities; stress-tests implementation; valuation practices revision; and revision of accounting treatment of financial instrument. Pillar 3 sets market discipline and disclosure requirements.

liquidity ratios: (i) the Liquidity Coverage Ratio (LCR) that should prevent a financial institution from a 30 days' period of liquidity crisis, (ii) and the Net Stable Funding Ratio (NSFR) making financial institutions able to face maturity mismatch risk.

In that way, we can notice at least three main developments specific to Basel III. The first one consists in giving a much more prominent place to liquidity matters which were absent from previous Basel agreements. A second important adjustment is the introduction of the concept of systemicity. Basel III aims at ending the "Too Big To Fail" paradigm by defining three groups of banks: global systemically important banks (GSIBs), domestic systemically important banks (DSIBs) and others. This means that not only does the new regulatory framework propose a measure of systemicity, but it also applied differently to banks depending on this measure. Indeed, in the Basel III logic, the more systemic a bank is, the more its default will induce important and spread negative consequences on the overall economy. Therefore, the more systemic a bank is, the stricter its regulation will be. The third important change implemented in the last regulatory framework is the introduction of a macroprudential strand. While microprudential regulation seeks both to ensure individual institutions stability and depositors and creditors' protection, the macroprudential part is aimed to provide financial stability limiting systemic risk (large perturbations having consequences on the real sphere) in a preventive perspective (Bennani et al., 2017). It works by adding capital or liquidity requirements, credit constraints, or taking measures against the shadow banking. This evolution, specific to the latest agreements, is crucial in the way that it gives more importance to the financial stability part of prudential regulation goals. The main purpose of improving financial stability is nevertheless a common denominator to all Basel reforms.

Moreover, there is a commonly accepted assumption among those agreements specifying that increasing prudential ratios is necessarily improving financial stability. However to the best of our knowledge, this hypothesis has only received very few attention from an empirical point of view. The economic literature has obviously already questioned the impact of prudential regulation but it has never assessed its empirical effect on financial stability. One of the major reasons explaining this lack of investigation is that defining and measuring financial stability is far from being trivial. A second important difficulty in analysing Basel agreements' impact, is the increasing complexity of regulatory framework. From this perspective, the presence of both interaction effects and nonlinearities emerges from the regulation-financial stability nexus, making it more challenging to investigate.

Therefore, our aim in this chapter is to assess empirically the hypothesis according to which an increase in prudential ratios leads to a more stable financial system. To this end, we propose our own financial stability composite index using a Principal Component Analysis. We account for the existence of potential nonlinearities in the impact of requirement ratios, and separate banks depending on their level of systemicity. More specifically, the main question we address in this chapter is: from an empirical point of view, do regulatory capital and liquidity requirements nonlinearly impact financial stability when accounting for systemicity levels?

Our contribution is plural: (i) we tackle a commonly accepted assumption among regulators stating that increasing requirement ratios improves financial stability, which has never been verified empirically; (ii) we propose a financial stability composite indicator; (iii) we investigate the nonlinearity of Basel III's impact; (iv) and we integrate systemicity in our approach which has not been widely studied. Relying on a sample of 23 countries, our results confirm the presence of nonlinearity in the financial stability - capital and liquidity ratios nexus. We also show that this relationship is not as automatic as the regulators' assumption suggests it. While we find that for low level of capital and liquidity, those ratios have a positive effect on financial stability, this impact partially disappears for higher levels. In addition, we show interconnexion between banks' subgroups confirming the relevance of separating banks according to their level of systemicity.

The remainder of the chapter is organized as follows: Section 1.2 reviews the related literature. Section 1.3 discusses financial stability matters and the construction of our financial stability indicator. We describe our data and methodology in Section 1.4. Section 1.5 displays descriptive statistics and tests. Results and robustness checks are presented in Section 1.6. Section 1.7 concludes.

1.2 A brief review of the literature

1.2.1 Prudential regulation impact [4]

Empirical literature

There are some attempts in the literature to assess empirically Basel III's impact. Kim and Sohn (2017), calculate the effect of liquidity and capital requirements on lending, using a fixed effect regression including interaction variables. They find a positive relationship between credit growth and increases in capital and bank liquidity. However this result only holds for large banks and was even more pronounced during the slump. Those authors show the existence of nonlinearity in the impact of capital on lending depending on the level of liquidity. Indeed, a cumulative effect was expected since both capital and liquidity have a positive impact on lending (Cornett et al., 2011; Carlson et al., 2013). Catalan et al. (2017) investigate a nonlinear effect of prudential regulation on lending, but they are focusing only on capital requirements. Their study is based on a theoretical framework in order to determine a loan growth rate expression that they use in an ARDL (auto-regressive distributed lag) model. The authors highlight that the impact of a bank recapitalization on loan growth depends not only on the initial level of capital but also on banks' strength. On their side, Giordana and Schumacher (2017) investigate the impact of Basel III liquidity and leverage requirements on Luxembourgian banks' risk default, measured by the z-score. They find, in a system-GMM analysis (system generalized method of moments), that if Basel

[4] See Tables 1.A.1 and 1.A.2 in appendix 1.A for a synthetic presentation.

III had been implemented before the crisis it would have cost 75 basis points of ROA (Return on Assets), but it would also have implied a decrease in default's probability.

Theoretical literature

In a theoretical modelling perspective, Krug et al. (2015) consider an agent-based credit network approach in order to assess the impact of Basel III in terms of financial system resiliency. In this article, financial stability is measured by the banking system's ability to survive over 500 crisis experiments. The study includes several requirements and gives results for a large set of initial conditions. The findings show that (i) the positive joint impact is larger than the sum of individual contributions, and (ii) macroprudential's impact is insignificant or negative, especially when looking at the systemic buffer. In addition, a significant number of studies use DSGE (dynamic stochastic general equilibrium) models in order to predict Basel III's impact following its implementation. Angelini et al. (2015), in the context of a BIS's (Bank of International Settlements) study, use that kind of model in order to assess the impact of the reform on the long term economic performance and fluctuations. They show a positive and marginally decreasing impact of Basel III requirements, meaning that an asymptotic limit exists in the reform's benefits. Those results are consistent with MAG (Macroeconomic Assessment Group; BCBS-MAG (2010)) and LEI (Long-term Economic Impact; BCBS-LEI (2010)) analyses. More recently, Quignon (2016) conducted a study reusing BIS's methodology taking into consideration real observations on Basel III's implementation to recalibrate Basel Committee's models. He finds that not only the marginal effect of regulatory requirements is decreasing but also that, beyond a certain limit, it becomes negative. Either way, this literature tends to underline the existence of a nonlinear impact of requirements depending on their level.

Studying systemicity

Because some banks are large enough to perturb a whole system in case of default, they are associated with the benefit of governmental guarantee. For this reason, the economic literature tends to support the idea according to which systemic banks increase their risk in order to augment their returns. Brandao et al. (2013) show that moral hazard emerges from public support to banks, especially during the recent crisis: risk accumulation in the United States was permitted by implied governmental warranty, while market participants get less suspicious considering that those banks will be bailed out in case of difficulties. The underlying idea is that the existence of a lender of last resort contributes to make large banks increase their risks (Gropp et al., 2013). These reasons prompted G20 to reconsider the "too-big-to-fail" status of certain banks and urged the Basel Committee to think a specific reglementation for systemic banks.[5] Shortly after, in November 2011, BCBS published a methodology to identify GSIBs, based on five criteria: size, interconnectedness, availability of substitutes, global activity and complexity (FSB, 2011; BCBS, 2011, 2013).

[5] Starting from 2010, international regulators initiated works in order to answer the "too-big-to-fail" issue and the quantification of systemicity (FSB, 2010).

Recent studies on systemicity under Basel III framework focus their analysis on GSIBs (not DSIBs). Moenninghoff et al. (2015) study the impact of GSIB requirements on the market value of large banks. In an event analysis, this paper gives a first look at the inexplicit aim of those rules, namely market discipline. Indeed, following designation events, negative abnormal returns appear for systemic banks meaning additional market cost for those banks. Schich and Toader (2017), in a difference-in-difference regression over 204 banks (of which 27 GSIBs) for the 2007 to 2015 period, show that GSIB treatment was not able to significantly reduce special government guarantees; although national tightening resolution practices were. Another difference-in-difference regression to analyse GSIB treatment effect is applied by Violon et al. (2017). Their assessment concludes that GSIB designation led to a very significant slowdown in the expansion of their balance sheets, improving leverage ratio and weighing on profitability, whereas risk weighted assets seemed to increase and no impact on yield have been shown. Overall, the literature tends to show that GSIB special treatment and designation are not neutral and have some effects on those banks. Therefore different banks have not the same impact on financial stability and must be differentiated.

Several conclusions can be drawn from this literature. Attempts in assessing the impact of regulatory reforms on financial stability are mainly analytical. Empirical studies are essentially looking at the effects on variables such as profitability or lending but rarely on financial system resiliency. No privileged methodology emerges from the empirical literature whereas theoretical analyses generally use DSGE models. Another aspect of those studies we noticed is the fact that few consider more than one component of Basel III reform and they generally show partition between micro- and macroprudential. Finally, whereas systemicity is at the center of Basel III, few investigations on this topic have been conducted. Our aim in this chapter is to overcome those limits of the literature in our empirical investigation. In addition to those general findings, the literature on regulatory impact financial stability seems to bring out two forms of nonlinearities, as detailed below.

1.2.2 Focusing on nonlinearities

Let us provide some economic intuitions regarding the presence of nonlinearities in regulatory requirements' impact on financial stability. First, as shown by both empirical (Kim and Sohn, 2017; Catalan et al., 2017), and theoretical (Krug et al., 2015; BCBS-MAG, 2010; Quignon, 2016) studies, standalone impacts are not additive. Second, benefits of ratios' increase diminish depending on the level of the concerned ratio: ratios' rises display an asymptotic limit.[6]

In a first place, reglementary public intervention is justified by the need to correct market imperfections: negative externalities, asymmetry of information, self-nuisance and monopolistic/oligopolistic market (Tirole, 2016). In this context, prudential regulation is aimed to both ameliorate stability and prevent from a systemic crisis. To do so, Basel III ratios are expected to answer several issues:

[6] Moreover, Quignon (2016) highlighted a trend reversal above a certain threshold.

(i) solvency ratios ensure perenniality of banks in the case of borrowers' default; (ii) liquidity ratios are aimed to support markets in terms of liquidity in a stress scenario and prevent banks from maturity mismatch risks; (iii) leverage ratios mitigate self-nuisance risks, GSIB surcharges are supposed to prevent from systemic and contagion risks, and disclosure requirements are thought in order to reduce information asymmetries and exacerbate market discipline.

It shoud not be believed that each rule or ratio answers a single stability problem. Actually, every requirement can have an effect on several criteria supporting financial stability. For instance, almost every ratio will help preventing from systemic shocks after a bank's default; or detaining more cash (therefore improving High Quality Liquid Asset and Liquidity Coverage Ratio) is certainly brightening solvency, etc. This explains why one cannot consider the impact of ratios taken independently of each other (Krug et al., 2015): studying Basel III's impact, a variety of ratios should be taken into account. As stressed above, if both R1 and R2, two ratios, are preventing from a same risk then we will have to consider the impact of R1 conditionally to the level of R2 and upside down.

In a second place, another nonlinearity we identify from the literature lies in the impact of a ratio depending on its own level. As a matter, a large strand of the literature investigates the impact of prudential ratios on variables such as profitability and lending. For instance, Mundt (2017) shows that a negative relationship links liquidity to profitability. Moreover, Lee and Hsieh (2013*a*) find an ambiguous link between bank capital and profitability. In a context of exacerbated competitiveness with shadow banking, over-regulation could therefore lead to a weakening financial system. On the contrary, as the last crisis has shown, Basel II requirements were not enough to prevent and absorb an important economic shock. Economically, the marginally decreasing impact of prudential ratios can be justified by the fact that it could prevent banks from financing conveniently the economy. For instance, Bredl (2018) shows that in compensation to provisions for loss, banks offer higher origination rates. Therefore our intuition is the following one: increasing capital and liquidity requirement is essential to improve financial stability; but it is possible that reaching high levels, those ratios create negative externalities. Consequently, enhancing prudential regulation could not only mean increasing prudential ratios but also diversifying the risks taken into account.[7]

Our aim is to assess the implicit hypothesis made by regulators: increasing quality and quantity of capital and liquidity ensures financial stability. Reviewing the literature, we show that there might be two kinds of nonlinearities in Basel III's impact on financial stability: a nonlinearity in parameter for a given ratio, and another one in the influence of a ratio considering the level of the other.

[7] From this point of view, the regulation of shadow banking is a typical example.

1.3 Financial stability

1.3.1 Financial stability: survey and methodology for a composite indicator

Gadanecz and Jayaram (2009) highlight the fact that financial stability is as hard to define as to measure, even though researchers have been taking a serious interest in it for two decades.

The first difficulty in studying financial stability is to capture its definition. A common mistake made in the literature is to define financial stability through the lens of instability. From this point of view, financial stability would describe an economic environment which is not in a financial crisis situation, where volatility is high, or in which trust in the banking system is low. This methodology is often adopted in the analysis of early warning indicators (Bussiere and Fratzscher, 2006; Drehmann and Juselius, 2014).

The definition gave by Bennani et al. (2017) is as follows: “a financial system is stable when it is resilient to episodes of financial stress or real shocks”, in other words, resilient to systemic risk. But those authors also introduce the idea that this definition should consider the fact that a stable financial system is a prosperous environment. Indeed, as being in a slump context creates negative externalities and can generate vicious circles, evolving in a strong economic scope might generate positive dynamic on the overall system. But as true as this argument is, it raises an important issue that is the problem of quantifying qualitative measures.

An easier way to make the link between financial stability’s definition and its measure is to think in terms of systemic risk. In a comprehensive survey, Benoit et al. (2017) identify three main sources of systemic risk highlighted in the literature: systemic risk-taking (correlation risk, liquidity risk and leverage cycles); contagion (balance-sheet contagion, payment and clearing infrastructures, informational contagion); and amplification (liquidity crises, market freezes and runs). For each category and subcategory, they identify the theoretical framework and the regulation in place to counter each risk. What we can notice is the small number of listed policy evaluation studies. Indeed, since Basel III is a relatively recent agreement, not all policies have been studied. Apprehending systemic risk seems to take more place in the economic literature every year, responding to a need from regulators. The main issue remains the lack of an overall measure in the sense that the proposed ones are generally defined in function of risk type. As Benoit et al. (2017) underline, “more structural models would be useful to regulators”.

Regulators also try to better capture financial stability, as notably shown by the intensification of regulators’ financial stability reviews and their growing importance. We summarize some of them that have been published recently, to give an overview of regulators’ approach of financial stability (see Table 1.1).

Table 1.1 Regulators' recent "Financial Stability Reviews" overview

Jurisdiction	**Frequency**	**Variables/themes adressed recently**
BDF (2018)	Annually since 2006	April 2018: shadow banking and interconnectedness
BDI (2018)	Bi-annually since 2010	April 2018: approach by sector (macroeconomic, national and household / financial, monetary, banks and insurance)
ECB (2017)	Bi-annually since 2002	November 2017: NPL market, cross-border banking area, repo market, financial market volatility
Federal Reserve (2016)	Annually since 2014	February 2017: monitoring risk, systemic institutions, coordination
FSB (2018)	Monthly since 2009	January 2018: cross-border resolution, FinTech, reporting data, compensation tools
IMF (2018)	Bi-annually since 2002	April 2018: monetary policy and inflation, riskiness of credit allocation and house price synchronization
NBB (2017)	Annually since 2002	June 2017: same approach

RBA (2018)	Bi-annually since 2004	April 2018: interest rates and asset prices, credit trends, crypto currency, Basel III capital ratios

Sources: last Financial Stability Reviews of each regulator mentionned.

The large majority of those financial stability reviews gives an insight in particular sectors. Revealing financial instability in some areas, regulators can thereafter orientate their policy on those specific sectors. For instance, during their last financial stability review presentation (April 25th 2018), Banque de France expressed its desire to focus on shadow banking. But regulators are rarely proposing composite indicators that could take into account several sectors.

Gadanecz and Jayaram (2009) also make this observation in a survey in which they list developments on quantitative measures of financial stability. Furthermore, they classify key variables from regulators' financial stability reviews into six categories:

1. Real sector: GDP growth, government fiscal position and inflation
2. Corporate sector: total debt to equity, earning to interest and principal expenses, net foreign exposure to equity, corporate default
3. Household sector: household assets and debt, household income, debt service and consumption
4. External sector: real exchange rate, foreign exchange reserves, current account, maturity/currency mismatches

5. Financial sector: monetary aggregate, real interest rates, growth in bank credit, CDS spread, NPLs, concentration of systemic risk/ sectorial concentration

6. Market financial conditions: volatility, change in equity, market liquidity, house prices

Hence, we consider that financial stability cannot be studied using one sector measure apart from others. Following Gadanecz and Jayaram (2009), and the comprehensive co-written handbook on constructing composite indicators by OECD and European Commission-JRC (Joint Research Centre-European Commission, 2008), we rely on Principal Component Analysis (PCA) to build our financial stability indicator. It is worth mentioning that although Dumičić (2016) implemented a PCA to construct a systemic risk accumulation index, this methodology has not been widely used for our purpose.

1.3.2 Financial Stability Indicator (FSI)

Since no composite index can only consider one sector of the economy in order to measure financial stability, we rely on a Principal Component Analysis.[8] We first provide an overview on our expectations regarding the performance of the financial stability indicator in light of the economic conditions in the recent years. Then, we describe our database and procedure to calculate our FSI.

[8]See appendix 1.B for a presentation of this methodology and results.

1.3.2.1 Expectations

The positive momentum in the developed economies from 2004 to 2007 should reflect a relatively stable system.[9] However, it is highly likely that an indicator of the financial system resilience will decline during this period. At the beginning of the crisis, financial instability is intended to reach high peaks while FSI is supposed to rapidly decrease. During the slump and first political reactions, we expect a slowdown in the decline of the FSI followed by a progressive recovery. According to our literature review, this recovery should be nonlinear and marginally decreasing. We also expect that the FSI will reflect, at least for European countries, the debt crisis. Figures 1.1 and 1.2 summarize those intuitions.

Figure 1.1: expected growth rate of FSI

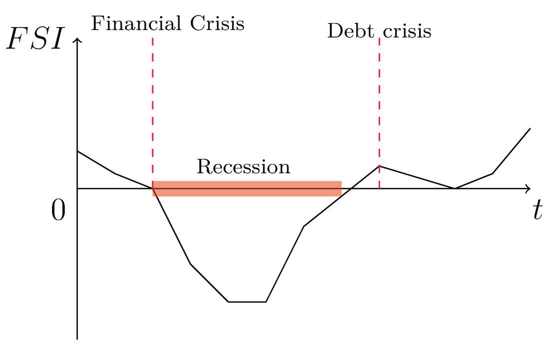
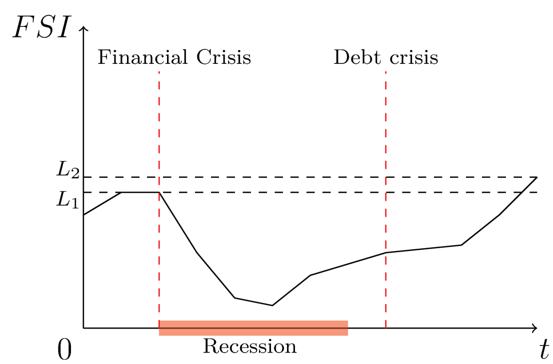


Figure 1.2: expected level of FSI



As can be seen, these figures show that financial stability is supposed to rise in the aftermath of the financial crisis. Especially, the behaviour of this increase is expected to be nonlinear (describing an asymptote in the long run), and it is intended that financial stability reaches a level superior to the one before the crisis.

[9]Note that financial instability could raise at the same time in the extent that a stable financial system can still be at risk. That what happened just before the recent financial crisis: while the system was characterised by a stable and prosperous environment, the risk of a crisis gradually increased until it triggered the financial collapse.

These two assumptions reflect (i) the results of the theoretical analyses conducted during the implementation of Basel III, and (ii) the regulators' own view that financial stability must be higher than its pre-crisis level (or at least move to a higher level) through regulation.

1.3.2.2 Financial stability indicator: a "two-steps" PCA

Because PCA does not support easily a large number of variables, we start by reducing the number of categories we consider.[10] Whereas Gadanecz and Jayaram (2009) distinguish six categories of variables representative of financial stability, we focus our analysis on the three following main sectors: real, financial and external. Our study goes from 2005 to 2016, for 23 countries.[11] Depending on the availability of data in space and time, we select a first set constituted by 20 variables (see appendix 1.B.1 for definition and sources). As 20 variables is a large number for a PCA, we select a dataset maximizing correlation in every pair of variables and keeping enough variables to account for the three sectors we retained.[12] This procedure leads us to select 12 variables: local and worldwide GDP, government debt and deficit, Treasury-Eurodollar spread, credit to non-financial institutions, non-performing loans and openness, monetary supply M3, financial stress, foreign reserves and VIX. For these variables we first build sub-indicators for each of the three sectors, and then run a PCA between those three sub-indicators. The

[10]Above all, let us note that we move the entire panel into growth rates, allowing us to guide our final interpretation of PCA results in terms of financial stability growth rates. This approach also serves as standardization of the sample, and establishes a common measure to all our variables.

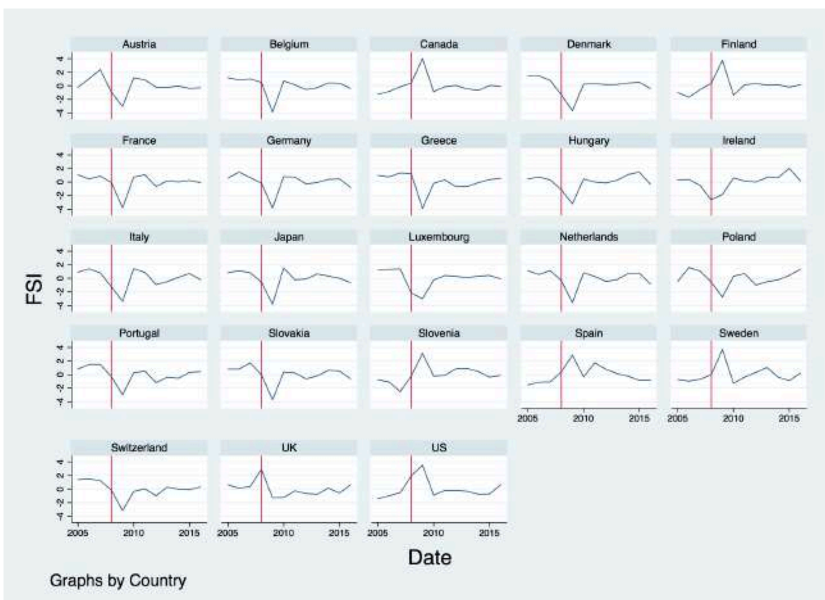
[11]Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom and United States.

[12]See the appendix 1.B.2 for details regarding our approach.

common component is therefore supposed to be the better part of financial stability we can extract from our dataset.

The approach we use in order to construct those intermediate indicators follows Nicoletti et al. (1999). It consists in running PCA among variables that compose the sub-group, retrieving the weights given by factor loadings after rotation and applying them to the group. Once this procedure is completed, we run a PCA using the three sub-indicators as the new variables. We implement a new correlation analysis to check that the correlation intra-groups remains enough elevated.[13] We keep the all 12 variables selected in the first correlation analysis and run a PCA in two steps to obtain our final FSI. Our results are presented in Figure 1.3.

Figure 1.3 – Financial Stability Indicator (growth rate) - PCA 2 steps



Source: author's calculations. Note: in red, 2008.

As shown, great geographical homogeneity is present in this analysis. Indeed, the

[13] Tables 1.B.2 and 1.B.3 in appendix 1.B.3 show how many times each variable is significantly correlated to an other one for every countries.

countries of Central, Southern and Eastern Europe present an indicator relatively close to our expectations.[14]

1.4 Data and methodology

1.4.1 Fitch Connect

We use the filters - accounting standards, consolidated data and country - provided by the database to select the data we need. For each bank of the 23 countries, we download data for more than 50 variables from 2004 to 2017. This procedure led us to retain 1646 banks, among which we have 31 GSIBs. The list of GSIBs is published every year by the Financial Stability Board, we retain all banks that have been at least once in this list. Our sample also contains DSIBs, the list of those banks being not as easy to find as the GSIBs one. For Europe we use the European Banking Authority's 2017 list, and retain 111 banks. For Canada we use the Office of Superintendent of Financial Institutions's list called "formally designated as DSIBs", leading us to select 6 DSIBs. Regarding the US, we use the BIS 2016 RCAP - Regulatory Consistency Assessment Programme - and the Federal Reserve's statistical release of large commercial banks. According to the Dodd-Frank act (2010), the Federal Reserve assesses the systemic importance of subsidiaries of foreign banking organisations with more than USD 50 billion in assets in US subsidiaries. We therefore apply this rule to the list released by the Federal Reserve, leading us to select 25 US DSIBs. The BIS's 2016 RCAP also

[14] In a robustness analysis, we also performed the one step PCA. The differences between countries in the indicator obtained with this one-step PCA are much more erratic and do not seem to reflect regional specificities.

gives us the 4 Japanese DSIBs.

In order to homogenize and balance our database as much as possible, we use banks' date of creation, study cases of merger and aquisition, and delete banks for which missing data was not justified by one of those two criteria. Applying those restrictions we retain 962 banks among which 31 GSIBs and 80 DSIBs. Because there is too many missing data in 2004 and because our FSI starts in 2005, we do not take this year into account.

In order to aggregate data at the national level, we use the following weighting method:

$$Weight_{i,t,l} = \frac{TotalAssets_{i,t,l}}{\sum_{j=1}^{n_{l,t}} TotalAssets_{j,t,l}}$$

Where $i \in [\![1; n_l]\!]$ designates the bank, $t \in [\![2005; 2016]\!]$ the date, $l \in [\![1; 23]\!]$ the country and $n_{l,t} \in \mathbb{N}$ the number of banks in the country l during the year t. Therefore the sum of all $Weight_i$ for a given t and l is always equal to 1 and the weight of all banks evolves between years in function of the banking system changes. The same method is used in order to aggregate data at subgroups levels (n_l becomes the number of banks in a subgroup for a given country).

Three proxys can be considered for capital and liquidity, respectively.[15] In order to select the two variables to be incorporated in the regression, we compare their evolution with those published by the regulators to focus our analysis on variables showing statistical coherence with what is observed by the BCBS and EBA. Specifically, all capital variables seem to follow the general trend of Basel III

[15]Capital: Total Equity, Common Equity and, Equity to Total Assets. Liquidity: Liquid Assets to Wholesale Funding, Liquid Assets to Total Assets, and Wholesale Funding to Total Funding.

capital requirements. We choose Equity to Total Assets, which is the more close to capital ratios. In order to perform robustness checks, we also estimate a number of regressions with Common Equity. Regarding liquidity, only Liquid Asset to Wholesale Funding follows the same trend as the Liquidity Coverage Ratio as it is relased by the BCBS and EBA.[16]

1.4.2 Control variables

To avoid an omitted variables bias, we also introduce control variables into the model. These are divided into two groups. On the one hand, we take into account the specific banking characteristics that may have an impact on financial stability. These variables are selected from those we have extracted from the FitchConnect database and we apply the same weighting method as for the variables of interest. The three candidate variables we use are the total loans granted by each bank, their income and their profit rate (measured by the Return On Assets). On the other hand, we control for macroeconomic effects introducing some variables related to financial stability that we have not included in the construction of our FSI indicator. We retain the interbanking interest rate (IIR), inflation rate and national banking Zscores.

1.4.3 Methodology

The baseline and interaction effect models

We aim at analysing the behaviour of the impact in variations of capital and

[16]See the Descriptive Statistics in Section 1.5.1.

liquidity on financial stability, using the FSI we constructed. Therefore, the baseline model we estimate is the following one:[17]

$$FSI_{i,t} = \alpha_i + \beta_1 Cap_{i,t} + \beta_2 Liq_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{1.1}$$

where FSI is our Financial Stablity Indicator, Cap and Liq are the main interest variables (capital and liquidity) and X is the vector of control variables.[18] α refers to the constant and ϵ is the error term. According to the literature we discussed earlier, we are expecting β_1 and β_2 to be positive.

The relation linking regulatory requirements and financial stability being potentially nonlinear, we introduce quadratic and interaction terms in this initial model following the standard literature on this kind of realtionship (Kim and Sohn, 2017). Remaining cautious about multicollinearity and interpretation issues associated with those terms, we refer to Balli and Sørensen (2013), as well as Chatelain and Ralf (2012) recommendations.[19] So, in a first step, we center the quadratic and interaction variables in order to facilitate the statistical interpretation of the estimated coefficients. In a second step we test for colinearity as well as for cross dependence. We then reproduce those two steps on the model with orthogonalized variables in the interaction term. In the case of all banks, those models are written as follows:[20]

[17] This baseline model will be called (1.2) for GSIBs, (1.3) for DSIBs and (1.4) for the other banks.

[18] Profitability, loans, inflation, national zscore and interbank interest rate.

[19] Those authors give recommandations regarding interaction effects and the risks of spurious regression when introducing variables that are highly correlated to each other into a model.

[20] See appendix 1.C.1 for the orthogonalized and the three other subgroups models.

$$
\begin{aligned}
FSI_{i,t} = \alpha_i + \beta_1 Cap_{i,t} + \beta_4(Cap_{i,t} - \bar{Cap}_{i,.})^2 + \beta_2 Liq_{i,t} \\
+\beta_5(Liq_{i,t} - \bar{Liq}_{i,.})^2 + \beta_6 Interac_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{2.1}
$$

where $Interac$ is the interaction term between capital and liquidity centered variables, and $v\bar{a}r_{i,.}$ refers to the intertemporal mean of each individual, with var detoning the considered variable. From now, centered variables will be called $CenterVar$. Note that models with interaction effect will be refered as $(2..')$. According to the literature, we should expect that β_1 and β_2 to be positive, while the coefficients associated to the quadratic terms should be negative. No sign is expected for the interaction term, but it should be logically positive, the idea being that the higher the ratios increase, the more their combined effect improves financial stability. Regarding sub-groups specifications, because the endogenous variable does not change from a model to another, we can give insight on the contribution of each category of banks to financial stability. From this point of view we expect that GSIBs coefficient will be higher than those associated to the two other types of banks.

Going further in the analysis of nonlinearity, we estimate a PSTR specification. This allows us to focus more precisely on the existence of the regimes mentioned in the literature, the value of the parameters in these regimes and the value of the threshold above which the reversal takes place. This method also makes it possible to study the influence of capital and liquidity between banking subgroups.

The panel smooth transition regression (PSTR) model

PSTR model is used to report on the individual or temporal heterogeneity of a relationship. Specifically, in this specification, the observations in the panel are divided into two regimes depending on whether a transition variable is lower or larger than a threshold value. PSTR is a generalization of the threshold model of Hansen (1999) to account for smooth and gradual transition between the two regimes. We seek to evaluate two types of nonlinearity that the PSTR can capture. On the one hand, we test the interaction of effects (the impact of a variation of one variable on the effect of another), and on the other hand, we evaluate the evolution of the behaviour of the effect of a variable according to its own the level. The PSTR meets these requirements and the heterogeneity we characterize takes the form of a continuous bounded function of a transition variable. For each category of banks, we estimate two PSTR models, depending on our variables of interest (liquidity or capital).

As shown in Table 1.D.4 displaying the Hausman (1978) test, the fixed effects specification is retained only for the GSIBs and DSIBs subgroups. As fixed effects must be included in PSTR, we estimate such models only for these two subgroups. To estimate the PSTR, we rely on Gonzalez et al. (2017) and we use the procedure implemented by Colletaz (2018) in RATS. As previously shown, capital and liquidity are expected to have a positive impact on financial stability, but in a decreasing way, so that this influence could become negative. In addition, we expect the effect of one ratio on the FSI to change with the level of the other. As stressed above, by allowing for heterogeneity, the PSTR makes it possible to invest these two points. The model is specified as follows:[21]

- GSIBs model:

$$
\begin{aligned}
FSI_{i,t} = \mu_i &+ \beta_1 GCap_{i,t} + \beta_2 GLiq_{i,t} + \beta_3 DCap_{i,t} + \beta_4 DLiq_{i,t} + \beta_5 OCap_{i,t} \\
&+\beta_6 OLiq_{i,t} + \beta_7 GX_{i,t} + (\beta_1^* GCap_{i,t} + \beta_2^* GLiq_{i,t} + \beta_3^* DCap_{i,t} \\
&+\beta_4^* DLiq_{i,t} + \beta_5^* OCap_{i,t} + \beta_6^* OLiq_{i,t}) g(Cap_{i,t};\gamma,c) + u_{i,t}
\end{aligned} \tag{3.1}
$$

- DSIBs model:

$$
\begin{aligned}
FSI_{i,t} = \mu_i &+ \beta_1 GCap_{i,t} + \beta_2 GLiq_{i,t} + \beta_3 DCap_{i,t} + \beta_4 DLiq_{i,t} + \beta_5 OCap_{i,t} \\
&+\beta_6 OLiq_{i,t} + \beta_7 DX_{i,t} + (\beta_3^* DCap_{i,t} + \beta_4^* DLiq_{i,t} + \beta_5^* OCap_{i,t} \\
&+\beta_6^* OLiq_{i,t}) g(Cap_{i,t};\gamma,c) + u_{i,t}
\end{aligned} \tag{3.2}
$$

where μ_i denotes individual fixed effects and $u_{i,t}$ is the error term. Cap refers to capital variable, Liq refers to liquidity variable, and X refers to control variables. Prefix G (respectively D and O) refers to GSIBs' variables (respectively DSIBs and Others). g is the transition function. It is continuous in the observable variable $Cap_{i,t}$ and normalized to be bound between 0 and 1. γ denotes the transition speed and c is the transition threshold. We follow the same procedure as in Gonzalez et al. (2017) by using the logistic specification for the function:

$$
g(Cap_{i,t};\gamma,c) = \left(1 + exp\left(-\gamma \prod_{j=1}^{m} (Cap_{i,t} - c_j)\right)\right)^{-1} \tag{4.1}
$$

[21] The general model, allowing for more than two regimes is written with an additive form (for capital as the transition variable): $FSI_{i,t} = \mu_i + \beta_0' Z_{i,t} + \sum_{j=1}^{r} \beta_j' Z_{i,t} g(Cap_{i,t};\gamma,c) + u_{i,t}$, where Z is the vector of interest variables and β are vectors of parameters. This form is used when implementing the specification tests.

Note that the specification is strictly the same for the model in which liquidity is the transtition variable, Cap being replaced by Liq in g. Those models will be refered as (3..').

It is worth mentioning that capital and liquidity variables of smaller groups are also interacted with the transition function, allowing us to account for the interaction between subgroups. We intend at controling for spillover effects from large banks to smaller ones, and therefore, for systemicity and in a way for contagion effects.

Before estimating the PSTR, several specification tests must be implemented. More specifically, tests are conducted (i) to assess homogeneity of the model, (ii) to select the most appropriate transition variable and (iii) to determine the most appropriate number m of regimes. In our case, two transition variables are considered, namely capital and liquidity. After the variables have been centered to eliminate the individual effects, the estimation of the parameters is performed by iteration using the nonlinear least squares method.

The last step of the PSTR procedure consists of two tests: constancy and no-remaining heterogeneity. To assess parameters' constancy we test the PSTR specification against a TV-PSTR (time-varying PSTR). To this aim, a second transition function is introduced in the model where the transition variable depends on time. It consists basically in testing if time has a significant effect in the nonlinear dynamic of the relation. The second test is for no remaining heterogeneity which is implemented in the same way as in the specification part. It aims at verifying that all the heterogeneity of the relation has been taken into account.

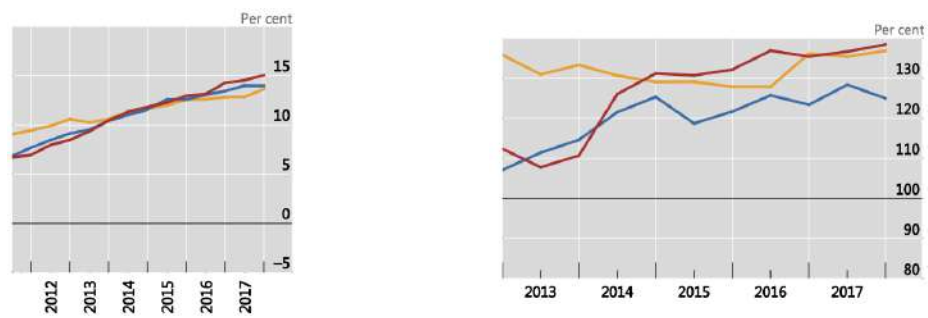
1.5 Descriptive statistics and specification tests

1.5.1 Descriptive statistics

We now present the variables of interest in our model, namely capital and liquidity. We begin by comparing the variables we selected from FitchConnect to the evolution of regulatory ratios published in BCBS and EBA reports. First, we present in Figures 1.4a and 1.4b the latest publications on the evolution of these ratios which are only calculated for the years 2010s.

Figure 1.4 – Capital (Tier 1) and liquidity (LCR) evolution over time and regions

(a) BCBS - Basel III monitoring report, October 2018



Source: BCBS. In red, blue and yellow, respectively, Europe, Americas and rest of the world.

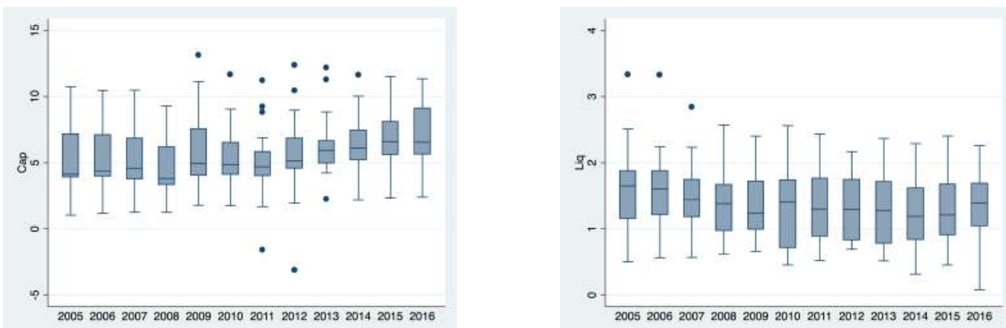
(b) EBA - CRD IV–CRR/Basel III Monitoring Exercise - March 2018

Source: EBA. Group 1 banks are banks with Tier 1 capital in excess of EUR 3 billion and which are internationally active. All other banks are categorised as Group 2 banks.

The overall observation is that capital and liquidity ratios have increased since the implementation of Basel III, the rise in capital being more frank than the increase in liquidity. In addition, while the short-term liquidity ratio of "small banks" in Europe has increased since 2011, this trend seems to have stopped since June 2014.

Figure 1.5 shows the evolution for all banks since 2010 of the variables we have selected to account for these regulatory ratios (see appendix 1.C.2 for the evolution of the three subgroups).

Figure 1.5 – Capital and liquidity - All banks - FitchConnect



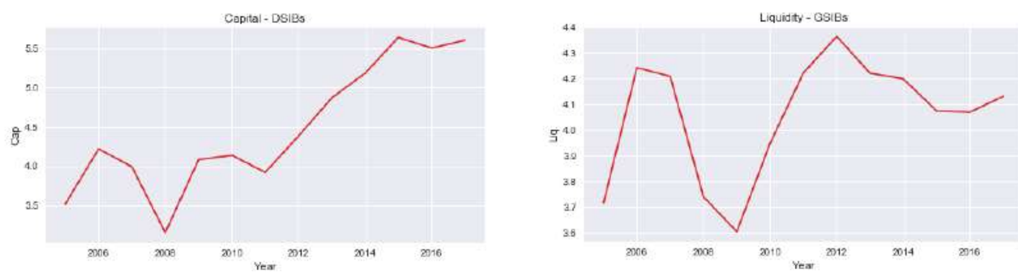
Source: Author's calculations from FitchConnect data.

As can be seen, our variables follow a trend close to regulators. However, several remarks can be made. First, the increase in capital is less pronounced. We rely on the ratio of equity to total assets, whereas Basel's solvency ratios use Risk Weighted Assets (RWA) as the denominator. As RWAs are lower than total assets, it is normal for our ratios to be lower than those in Basel. In addition, in order to meet regulatory objectives, regulated banks have sought to increase their ratios by augmenting the numerator (equity) while reducing the denominator (RWAs). We therefore capture the capital increase but not the decrease in weighted assets. On the contrary, for many banks total assets have tended to rise since the crisis.

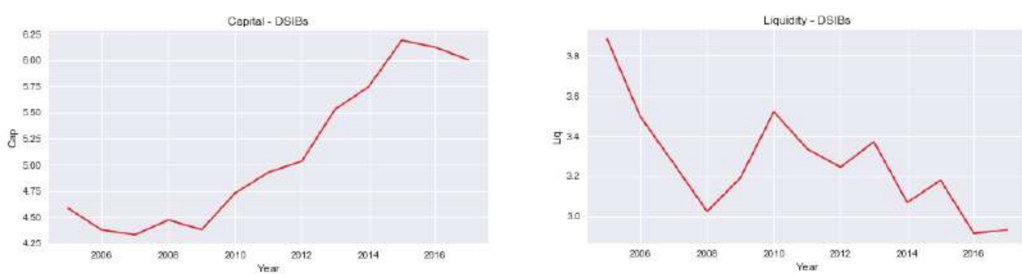
Second, the liquidity variables are expressed in logarithmic terms[22] in order to cushion the large disparities that could arise between countries. An increase can be perceived while remaining largely smaller than the one observed in EBA and BCBS publications. In order to better highlight the general trends we display in Figures 1.6a to 1.6c medians of capital and liquidity variables for each banks subgroups.

Figure 1.6 – Capital and liquidity medians

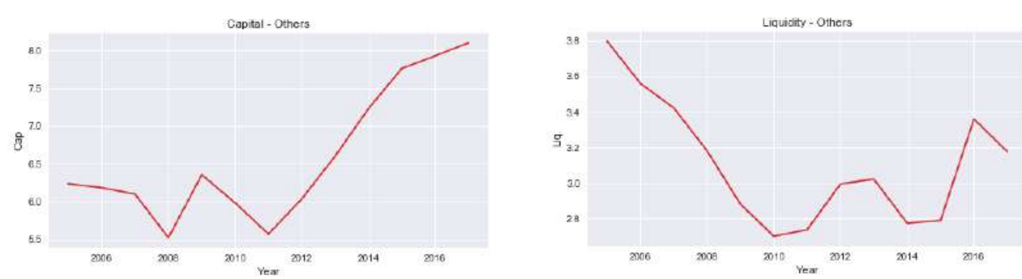
(a) GSIBs - FitchConnect



(b) DSIBs - FitchConnect



(c) Others - FitchConnect

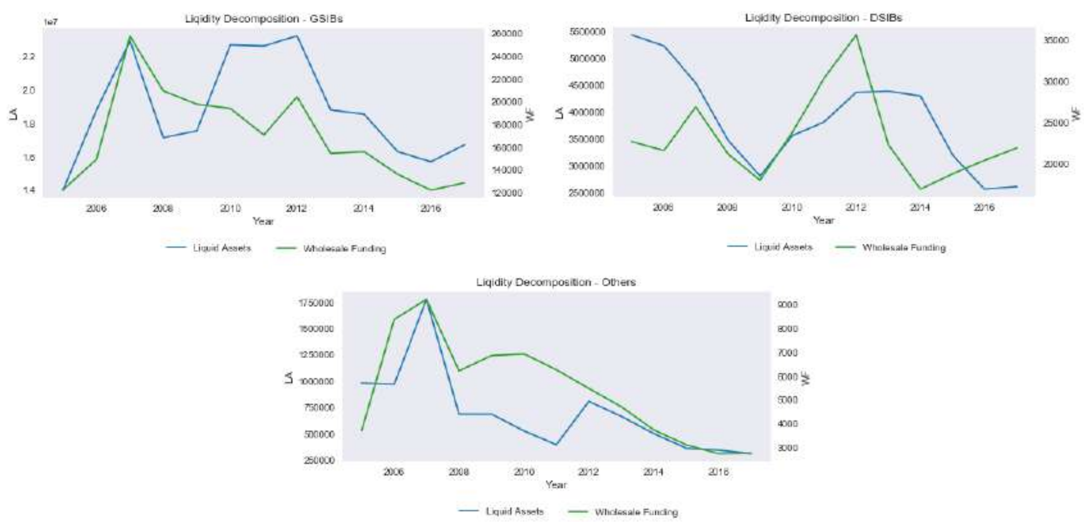


We notice that capital variables seem to follow the same trend as those disclosed

[22]Explaining why those values are so low.

by regulators. However, even if for GSIBs our liquidity proxy shows a positive trend as expected, the same conclusion cannot be drawn for the other two groups of banks. For DSIBs and small banks, liquidity decreases describing less continuous movements. To better understand those observations we break down liquidity ratios in Figure 1.7 (see Figure 1.C.4 in appendix 1.C.2 for the capital case).

Figure 1.7 – Breaking down liquidity proxies - FitchConnect



Source: Author's calculations from FitchConnect data.

As can be seen, all three ratios show decreasing numerator and denominator. The fact that liquid assets (numerator) is declining slower than wholesale funding in the GSIBs case explains why the GSIBs ratio follows a trend closer to the one expected. For both DSIBs and small banks, liquid assets are declining more rapidly than wholesale funding. It explains the decrease in their liquidity ratios. As shown, liquid assets have negative trends for a large part of our sample, going against what is observed from the LCR. This results from the fact that the numerator of LCR is only composed of high quality liquid assets. Our liquid asset variable accounts for more asset classes and may therefore show a different trend, we thus have to be cautious in the interpretation of our results regarding liquidity.

1.5.2 Specification tests [23]

There is a debate on the need to test for non stationarity in panel data, as discussed in Baltagi (2008). This debate was born with the growing possibility of being able to extend the temporal dimension of the panels calling into question the supposed homogeneity of pooled regressions. As we are dealing with part of a micro-panel (12 observations for 23 individuals), we are not concerned by these issues. However, for the sake of completeness and rigour, we check the stationarity of our variables. As shown in appendix 1.D.2, although the results are somewhat mixed, we do not transform our original series as (i) we work on a micro panel and (ii) some variables are ratios, which are by definition bounded.

As discussed above, the introduction of quadratic and interaction terms can create multicollinearity within the model. Although we control for this effect by orthogonalizing the terms in the interaction variable (as recommended by Balli and Sørensen (2013)), we check for the absence of collinearity using VIF (Variance Inflation Factor).

For all models we find evidence that profitability and income, when simultaneously included in the regression, are at the origin of multicollinearity. Therefore, we remove income from all models.

[23] The results from specification tests are reported in appendix 1.D.

1.6 Results

1.6.1 The baseline model: results of the linear specification

As shown in Table 1.2, the model (1.1) involving all banks is not conclusive, probably due to the aggregation of bank groups. The capital variable, on the other hand, is significant for models involving GSIBs and DSIBs: it has a small but positive impact on financial stability for both groups. An increase in capital therefore improves financial stability. The same remarks hold about liquidity. Regarding the model (1.4) with small banks, results for capital and liquidty appear no significant which could be due to the fact that this group contains too small and too few banks to capture the impact of their prudential ratios on financial stability.

Table 1.2 Results - Linear Model

Variables	Models			
	(1.1) All	(1.2) GSIBs	(1.3) DSIBs	(1.4) Others
	re	fe	fe	re
Capital	-0.013	0.445**	0.704***	0.038
	(0.865)	(0.016)	(0.001)	(0.316)
Liquidity	-0.062	1.536***	0.800*	-0.033
	(0.845)	(0.005)	(0.053)	(0.003)
Profitability	0.265**	-0.729**	-0.807***	0.176***
	(0.017)	(0.041)	(0.010)	(0.003)
Loan	-0.057***	-0.054***	-0.063***	-0.018**
	(0.001)	(0.002)	(0.004)	(0.033)
IIR	0.086	0.303	0.214**	0.119*
	(0.212)	(0.015)	(0.030)	(0.079)
Inflation	0.105*	-0.080	0.057	0.081
	(0.072)	(0.516)	(0.645)	(0.163)
Zscore	-0.044	-0.037	-0.088	-0.081**
	(0.258)	(0.535)	(0.177)	(0.016)
Constant	101.855***	97.734***	98.887***	100.3285***
	(0.000)	(0.000)	(0.000)	(0.000)

Source: Author's calculations. Note: p-values in parentheses. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively. fe and re refer to fixed effects and random effects respectively.

1.6.2 Accounting for interaction effects and quadratic terms

Results of the polynomial models with interaction effects ((2..)) are reported in Table 1.3. Confirming the findings obtained with the linear specification, when aggregating all banks (model (2.1)), no significant effect appears between capital and liquidity ratios and financial stability. Moreover, the absence of significant effect in the model with small banks is also confirmed in the polynomial model with interaction variable (2.4). It corroborates our intuition that this groups contains too small and too few banks for the model to capture its effect.

Regarding models (2.2) and (2.3), the effect of capital at low levels is positive and significant, in line with the literature: variations of systemic banks' capital improves their solvency and therefore financial stability. In the GSIBs model we also remark that the effect of capital remains significant for high levels: the coefficient associated with the capital quadratic term is negative and smaller than the simple coefficient in absolute terms. This finding is in line with the economic literature in both ways: (i) it corroborates the presence of nonlinearity, and (ii) it is consistent with BCBS-MAG (2010) and Quignon (2016) results regarding the existence of a decreasing effect of the benefit from capital ratios' increase. The impact of liquidity ratios is not as perceived as capital's one. As already mentioned, this is explained by the low variations of our liquidity variable. However, these ratios have a positive influence for low levels in the GSIB model, suggesting that this group contains banks that are large enough for their liquidity ratios (as we measure it) to influence significantly financial stability. The significance of the interaction term in the model with DSIBs might suggest that this group is constituted of banks that have more difficulties in achieving regulatory objectives simultaneously. Consequently, the increase in one ratio may affect their ability to maintain the other through profitability, monitoring or internal managerial policy constraints. With more flexibility, GSIBs can more easily adjust different ratios at the same time, which explains the lack of significance of the interaction term for this group of banks. This confirms that the more systemic a bank is, the higher its influence on financial stability. We will test this intuition in the PSTR regression. Finally, profitability has a negative and significant impact on financial stability in line with the literature dealing with the pursuit of risk.

Overall, our results show that the more systemic a bank is, the more the impact of its capital on financial stability is important. This is consistent with Basel III regulatory framework. But we also show that, at least for GSIBs, there is a turning point in the trend from which the marginal effect of an increase in capital becomes negative. Our interpretation is that GSIBs play a substantial role in financing a large set of diversified activities. Therefore constraining them could create viscosities in the financing market. Let us now investigate this finding in more detail through the estimation of the PSTR model.

Table 1.3 Results - Polynomial Model with Interaction Effects

Variables	Models - Before Orthogonalization											
	(2.1) All			(2.2) GSIBs			(2.3) DSIBs			(2.4) Others		
	re			fe			fe			re		
Capital	-0.002	0.021	0.020	0.413**	0.486***	0.459**	0.837***	0.734***	0.846***	0.028	0.033	0.028
	(0.976)	(0.790)	(0.813)	(0.024)	(0.009)	(0.014)	(0.000)	(0.001)	(0.000)	(0.465)	(0.418)	(0.487)
Liquidity	-0.070	0.020	0.026	1.236**	1.281**	1.100*	0.222	0.758*	0.187	-0.017	-0.005	-0.004
	(0.828)	(0.950)	(0.935)	(0.031)	(0.023)	(0.058)	(0.617)	(0.067)	(0.678)	(0.924)	(0.976)	(0.981)
Interaction	0.068	-	-0.017	-0.843*	-	-0.678	-1.606***	-	-1.528***	0.048	-	0.034
	(0.703)		(0.925)	(0.088)		(0.239)	(0.004)		(0.007)	(0.129)		(0.392)
Capital^2	-	0.036**	0.036**	-	-0.212**	-0.168	-	-0.209*	-0.138	-	0.002	0.001
		(0.015)	(0.016)		(0.050)	(0.140)		(0.250)	(0.250)		(0.695)	(0.851)
Liquidity^2	-	-0.846	-0.841	-	0.143	0.591	-	-0.573	-0.833	-	-0.253	-0.135
		(0.215)	(0.218)		(0.877)	(0.553)		(0.467)	(0.282)		(0.171)	(0.557)
Profitability	0.280**	0.332***	0.328***	-0.668*	-0.890**	-0.791**	-0.569*	-0.956***	-0.679**	0.185***	0.169***	0.179***
	(0.018)	(0.004)	(0.006)	(0.060)	(0.015)	(0.034)	(0.068)	(0.003)	(0.039)	(0.002)	(0.005)	(0.004)
Loan	-0.058***	-0.064***	-0.064***	-0.064***	-0.056***	-0.062***	-0.103***	-0.079***	-0.115***	-0.018**	-0.0197**	-0.019**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.035)	(0.030)	(0.033)
IIR	0.088	0.103	0.103*	0.301**	0.371***	0.350***	0.272***	0.326***	0.301***	0.126*	0.121*	0.125*
	(0.202)	(0.135)	(0.138)	(0.015)	(0.004)	(0.007)	(0.006)	(0.010)	(0.003)	(0.063)	(0.074)	(0.066)
Inflation	0.102*	0.090	0.090	-0.109	-0.116	-0.131	0.043	0.033	-0.065	0.100	0.078	0.068
	(0.083)	(0.127)	(0.127)	(0.378)	(0.348)	(0.293)	(0.720)	(0.793)	(0.785)	(0.268)	(0.179)	(0.251)
Zscore	-0.047	-0.057	-0.057	-0.042	-0.039	-0.0461	-0.102	-0.065**	-0.086	-0.084**	-0.084**	-0.085**
	(0.238)	(0.146)	(0.154)	(0.478)	(0.509)	(0.448)	(0.108)	(0.320)	(0.184)	(0.013)	(0.013)	(0.012)
Constant	101.88***	102.0***	101.98***	99.09***	98.4***	99.18***	101.29***	99.61***	101.95***	100.44***	100.47***	100.51***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Source: Author's calculations. Note: p-values in parentheses. fe and re refer to fixed effects and random effects respectively.
Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

1.6.3 Nonlinearities and cumulative impact: results of the PSTR regression

The first step consists in testing homogeneity and nonlinearity. As shown in Tables 1.E.3 and 1.E.4 in appendix 1.E.1, homogeneity is rejected and two regimes are retained for the two transition variables. Table 1.4 reports the results of PSTR estimation[24] and Figures 1.8 to 1.11 display the transition functions.

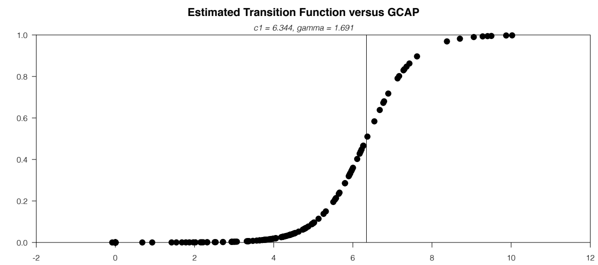
Table 1.4 PSTR - estimation resuts

Model - Q	(3.1) - Capital		(3.1') - Liquidity		(3.2) - Capital		(3.2') - Liquidity	
Variable	Coeff	Robust SE	Coeff	Robust SE	Coeff	Robust SE	Coeff	Robust SE
Coefficients in the first regime (effect for low values of the transition variable)								
Profitability	-0.694***	0.265	-0.814***	0.287	-0.569*	0.343	-0.537	0.333
Loan	-0.037***	0.013	-0.035**	0.014	-0.124***	0.029	-0.102***	0.029
Inflation	0.054	0.052	0.053	0.053	0.088	0.055	0.038	0.057
Zscore	-0.068	0.046	-0.065	0.049	-0.102**	0.079	-0.105**	0.049
IIR	0.286***	0.074	0.274***	0.077	0.256***	0.073	0.318	0.080
GCAP	0.027	0.180	0.674***	0.166	0.318*	0.166	0.154	0.154
GLIQ	1.568***	0.499	2.192***	0.715	0.794	0.537	1.237**	0.553
DCAP	0.116	0.145	0.161	0.168	1.623**	0.840	0.600***	0.159
DLIQ	-0.006	0.376	-0.012	0.455	1.731	1.598	1.592***	0.534
OCAP	0.079**	0.041	0.060	0.044	0.096**	0.043	0.069	0.049
OLIQ	0.119	0.175	-0.028	0.182	-0.116	0.184	-0.167	0.186
Coefficients in the second regime (effect when the transition variable increases)								
GCAP$\times g(Q,\gamma,c1)$	0.226	0.704	-0.835***	0.287	-	-	-	-
GLIQ$\times g(Q,\gamma,c1)$	-0.875	2.280	0.223	0.846	-	-	-	-
DCAP$\times g(Q,\gamma,c1)$	0.677	0.438	0.214	0.232	-0.734	0.847	-0.481***	0.198
DLIQ$\times g(Q,\gamma,c1)$	1.532	1.518	-0.172	0.657	-1.739	1.588	-1.557	0.626
OCAP$\times g(Q,\gamma,c1)$	0.497	0.384	-0.116	0.156	-0.326***	0.116	0.053	0.039
OLIQ$\times g(Q,\gamma,c1)$	-4.643***	1.930	1.000	0.517	0.785*	0.447	1.891***	0.497
Sum of coefficients when transition=1 (overall effect, both regimes taken into account)								
GCAP	0.253	0.725	-0.161	0.262	-	-	-	-
GLIQ	0.692	2.302	2.416***	0.843	-	-	-	-
DCAP	0.794*	0.470	0.376	0.231	0.889***	0.180	0.118	0.212
DLIQ	1.526	1.398	-0.184	0.483	-0.008	0.374	0.035	0.641
OCAP	0.577	0.380	-0.056	0.151	-0.230**	0.107	0.122***	0.043
OLIQ	-4.524***	1.909	0.971**	0.505	0.669	0.409	1.723***	0.474
γ	1.691	0.317	105.707	79.805	5.053	1.275	15.695	0.000
c_1	6.343	0.287	1.848	0.011	2.999	0.082	1.675	0.0352

Source: Author's calculations. g refers to the transition variable. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

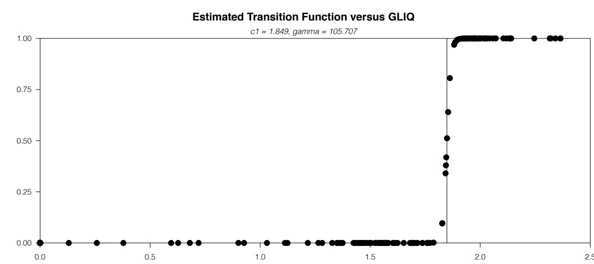
[24] We do not report the estimation of model (3.3') due to convergence issues.

Figure 1.8 – Transition function - Capital - model (3.1)



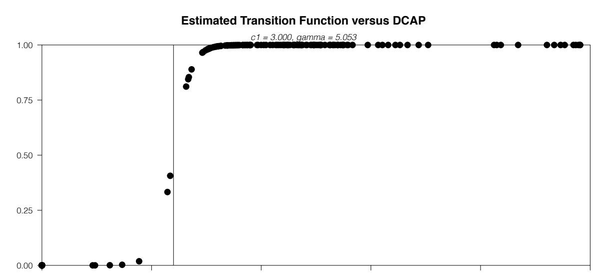
Source: Author's calculations.

Figure 1.9 – Transition function - Liquidity - model (3.1')



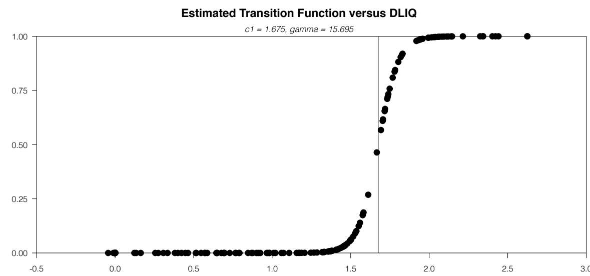
Source: Author's calculations.

Figure 1.10 – Transition function - Capital - model (3.2)



Source: Author's calculations.

Figure 1.11 – Transition function - Liquidity- model (3.2')



Source: Author's calculations.

Looking at GSIBs (models (3.1) and (3.1')), capital and liquidity appear positive and significant for low levels of both transition variables. It confirms the regulators' intuition: increasing regulatory ratios improves financial stability. Nonlinearity in the dynamics of capital and liquidity impact is not captured by the model. Indeed, if the impact of those ratios has an asymptotic limit, it should be more difficult to capt their effect for high values. Moreover, no negative significant impact is captured either, which leads us to reject the hypothesis that there is a reversal of the impact of regulation on stability. Regarding interaction effects, model (3.1') shows that there is a significant and negative effect of liquidity on capital's impact, equal to -0.835, while the opposite is not true. The overall impact of GSIBs' liquidity is found significant and positive in the model (3.1'), equal to 2.416. This corroborates the results of the polynomial model (2.2): GSIBs' liquidity has a significant impact on financial stability.

Those results are consistent with our intuitions and with the economic literature: (i) the impact of a ratio marginally decreases as this ratio increases, and (ii) the accumulation of rules can create negative externalities. The transition appears smooth in the model (3.1) with capital as a transition variable (see Figure 1.8), and the threshold ($c_1 = 6.343$) is in line with the literature.[25] However, the transition function in the model (3.1') shows abrupt transition with few observations in the second regime (see Figure 1.9). We attribute this finding to our liquidity measure as the logarithmic transformation may have overwritten the transition speed.

Regarding models (3.2) and (3.2') which assess nonlinearities in DSIBs' ratios, results also confirm that for low levels, capital and liquidity improve financial stability. Regarding the impact in the second regime (with high values for both transition variables), findings are similar to those obtained with the GSIB model: (i) each ratio has a marginally decreasing, but not negative, impact (which can be seen by the absence of strong significant effect for high values of capital and liquidity), and (ii) an interaction negative effect appears from liquidity to capital (with a coefficient of -0.481). Note that, as shown by Figure 1.10, the low regime contains very few observations, a fact that may explain the low threshold value in the case of capital as a transition variable.

Regarding the interactions between groups of banks, capital of both GSIBs (-4.643) and DSIBs (-0.326) impacts negatively the group of small banks, while liquidity has positive effects (0.971 for GSIBs and 0.122 and 1.723 for DSIB effect on small banks). This could be explained by the fact that if important banks are highly resilient on a liquidity point of view, small banks have better access to the interbank market and therefore meet their regulatory requirement easier. On the other hand, capital ratios concern the way a bank finance itself. Therefore, it

[25] In fact it is slightly too low, which is related to the fact that our numerator is composed of total assets and not risk-weighted assets only.

might be possible that the more important banks have to provision their capital, the fewer are opportunities for smaller banks to finance themselves.

It is worth mentioning that for all models, bank profitability has a significant and negative impact on stability. This can be explained by the fact that the pursuit of profit sometimes encourages risk-taking behaviours that lead to an increase in exposure. These findings corroborate those obtained with the interaction effect model. Finally, as shown in Table 1.E.5 in appendix 1.E.2, our models are well specified since in each case, the alternative TV-PSTR model is rejected, and it seems that all heterogeneity has been taken into account.

1.6.4 Robustness checks

We check for the robustness of our findings to the choice of the endogenous variable.[26] Specifically, we consider two variables, which are representative of part of financial stability: the Interbank Interest Rate (IIR) and the national bank Zscore.[27]

As shown in Table 1.5,[28] the variables of interest in the model (2.1*), when considering IIR as the dependent variable, are not significant, corroborating the fact that an aggregated model cannot take into account each group special characteristics. In the GSIB model (2.2*), results obtained are in line with the interaction model (2.2): the effect of capital ratio on IIR, -0.809, is negative and significant for low levels and becomes positive but absolutly lower for high levels taking a

[26]Note that using orthogonalization to control for cross-dependence and multicolinearity lead to similar results.
[27]IIR is representative of interbank trust in each other and Zscore of the distance to default. Therefore, an improvement of financial stability corresponds to a decrease in IIR and an increase in Zscore.
[28]We only report the results with interaction effects, due to convergence issues with the PSTR specification.

Table 1.5 Robustness - Polynomial Model with Interaction Effect

Variables	(2.1*) All		(2.2*) GSIBs		(2.3*) DSIBs		(2.4*) Others	
	fe	fe	fe	re	fe	re	re	fe
	IIR	Zscore	IIR	Zscore	IIR	Zscore	IIR	Zscore
Capital	-0.408***	1.094***	-0.809***	0.572**	-0.615***	1.283***	-0.053*	0.315***
	(0.000)	(0.000)	(0.000)	(0.027)	(0.001)	(0.000)	(0.063)	(0.000)
Liquidity	0.011	-1.365***	0.284	-4.257***	0.134	-3.327***	0.426***	0.265
	(0.969)	(0.002)	(0.484)	(0.000)	(0.746)	(0.000)	(0.007)	(0.425)
Interaction	-0.269	0.766***	-0.633	-0.779	0.850*	-0.522	-0.045	0.039
	(0.107)	(0.002)	(0.117)	(0.342)	(0.094)	(0.446)	(0.219)	(0.569)
Capital^2	-0.008	0.054***	0.258***	0.005	0.260**	0.412**	-0.004	-0.009
	(0.558)	(0.007)	(0.001)	(0.972)	(0.017)	(0.011)	(0.462)	(0.365)
Liquidity^2	1.201*	1.554*	0.593	1.734	-0.064	0.039	-0.105	0.089
	(0.054)	(0.092)	(0.398)	(0.227)	(0.927)	(0.970)	(0.617)	(0.825)
Profitability	0.430***	0.549***	1.694***	1.872***	0.789***	1.214***	-0.000	0.286***
	(0.000)	(0.044)	(0.000)	(0.000)	(0.007)	(0.005)	(0.001)	(0.007)
Loan	0.004	0.048*	-0.004	-0.032	0.033	-0.067**	2.26e-06	0.035*
	(0.136)	(0.056)	(0.748)	(0.208)	(0.164)	(0.027)	(0.917)	(0.091)
Inflation	0.481***	-0.189**	0.365***	-0.146	0.480***	-0.013	0.517***	-0.308***
	(0.000)	(0.018)	(0.000)	(0.417)	(0.000)	(0.935)	(0.000)	(0.002)
Zscore	-0.006	-	-0.135 ***	-	-0.158***	-	-0.057***	-
	(0.692)		(0.001)		(-0.158)		(0.007)	
IIR	-	0.037	-	-0.577***		-0.379***	-	-0.174
		(0.692)		(0.001)		(0.003)	-	(0.136)
Constant	2.511**	5.561***	5.055***	11.298***	3.683**	14.087***	1.310***	8.211***
	(0.019)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.009)	(0.000)

Note: p-values in parentheses. fe and re refer to fixed effects and random effects respectively. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

value of 0.258. In the model with DSIBs, we also find that low levels of capital ratio impact positively the IIR, the coefficient being equal to -0.615, and that high levels of capital impact negatively the IIR (0.260). In model (2.4*) with small banks, the impact of capital on financial stability as proxied by IIR is negative for low levels but not significant for high levels. Liquidity's impact is either too small or unperceived in all models due to lack of variations, consistent with our previous observations. Those findings using IIR as the dependent variable are all corroborating our previous results, as well as those obtained in the literature.

Turning to the case where financial stability is proxied by Zscore,[29] the results

[29] For the sake of transparency, note that as Zscore integrates profitability which is also introduced as a control

for capital and liquidity ratios in subgroups models are in line with our previous findings and the literature. Capital has a positive and marginally decreasing impact on financial stability: in the case of GSIBs the impact is positive for low levels of capital and becomes non-significant when getting higher, and in the case of DSIBs, the impact of capital is positive in both regimes but becomes lower for high values of capital (going from 1.283 to 0.412). However, liquidity shows strong negative and significant effect which is in contradiction with our previous results and the literature.

In both models, the interaction effect shows unperceived impact on financial stability. Finally, for all models, our findings confirm that banks' profitability is an important determinant of financial stability.

1.7 Conclusion

In this chapter, we aim at investigating regulators' assumption, stating that increasing banks' capital and liquidity improves financial stability. To this end, we propose a measure of financial stability based on a principal component analysis, and explain this composite indicator using capital and liquidity variables. Paying particular attention to nonlinear effects of these variables on financial stability, we estimate a polynomial model with interaction effects and a panel smooth transition regression model.

variable, in its calculation, endogeneity issues may be at play. The interpretation of the models is thus subject to some caution.

Our findings show that the impact of capital on financial stability is nonlinear: capital has a positive impact on financial stability for low levels, and this effect becomes weaker in most cases when capital increases. Turning to the liquidity variable, the same conclusion can be drawn. We find that interactions exist between groups of banks, going from important banks to smaller ones. We also show that the impact of prudential ratios on financial stability is different from a group to another. This justifies regulators' approach of treating important banks (GSIBs and DSIBs) differently. Finally, we show that profitability plays a significant role in financial stability.

Our findings have important policy implications. First, it is mandatory for regulators to have the necessary tools to carry out an assessment of the rules they put in place. Measuring financial stability by variables referring to regulatory requirements that are intended to improve financial stability - as proposed by the IMF - does not seem fully satisfactory. From a resiliency point of view, regulators should propose an aggregated and comprehensive measure of financial stability, which could evolve in time according to economic developments and new springs of instability. In this way, reglementation could prevent the economy from new shocks and prepare it to absorb them. Second and following the work carried out by the FSB since 2017, there is a need to assess the impact of regulations in order to adjust them if necessary to ensure the stability of the system. This analysis must account for nonlinear effects, in particular interactions between rules.

A promising extension of this chapter would be to work on non-aggregated banks, by analysing the impact of capital and liquidity ratios on individual z-scores. By the way, this will increase the number of observations and, in turn, improve the reliability of our findings. Finally, integrating contagion effects in the analysis will be of interest for future research to account for resiliency, in particular when measuring financial stability.

Appendix

Appendix 1.A Literature review

Table 1.A.1 Literature: Basel III impact, nonlinearities

Authors	Variables	Impact/result	Type	Model and Data
Angelini et al. (2015)	Cap, liq, buffer	NL ⊕	Analytical	DSGE
Carlson et al. (2013)	Cap, LR, loan growth	⊕	Empirical	FE, MSA-FE, US, 2001-2009, FDIC and Call reports
Catalan et al. (2017)	Cap, lending	NL ⊕	Empirical	FE, 2SFE, Indonesia, 2001Q1-20015Q4, Bank of Indonesia
Cornett et al. (2011)	Cap, liq, loan groth, credit	⊕	Empirical	FE, US, 2006Q1-2009Q2, Call Reports and FFIEC
Giordana and Schumacher (2017)	Z-score, ROA, cap, liq	⊕/⊖	Empirical	Sys-GMM, 2003Q2-2011Q3, BCL
Kim and Sohn (2017)	Cap, liq, loan growth	NL ⊕/⊖	Empirical	FE, US, 1993Q1-2010Q4, FDIC SDI
Krug et al. (2015)	Cap, liq, LR, GSIB	NL ⊕/⊖	Analytical	Agent-Based Model

Table 1.A.1 (continued)

Lee and Hsieh (2013*a*)	CAP, Profitability	⊕/⊖	Empirircal	GMM
Mundt (2017)	Liqu, profitability	⊖	Empirical	GMM
Quignon (2016)	Cap, Liq, GDP, GSIB	NL ⊕/⊖	Analytical	DSGE
Tirole (2016)	-	-	Book	Market imperfections

Note: DSGE, Dynamic Stochastic General Equilibrium; PP, position paper; LR, Leverage Ratio; FE, fixed-effects; MSA-FE, Measurement system analysis FE; 2SFE, Two Step FE; NL, Nonlinearities; GMM, Generalized Method of Moments. ⊕/⊖: positive/negative effect

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Table 1.A.2 Literature: Systemicity

Authors	Type	Method	Content
BCBS (2011, 2013), FSB (2011)	RP	Arithmetical average on market share	GSIB designation: calculation of GSIB score.
Brandao et al. (2013)	Empirical	FE - IV	Government guarantees positive impact on Moral hazard.
FSB (2010)	RP	-	Quantification of systemicity.
Gropp et al. (2013)	Empirical	SUR	Removal of a government guarantee negative impact on risk-taking.
Moenninghoff et al. (2015)	Empirical	Event study	GSIB special treatment negative impact on market value.
Schich and Toader (2017)	Empirical	Diff-in-diff	No significant impact of GSIB treatment on government guarantee. Positive impact of national resolution.
Violon et al. (2017)	Empirical	Diff-in-diff	Negative impact of GSIB treatment on balance sheet expansion and on profitability. No impact on yield.

Note: RP, Regulation Paper; FSB, Financial stability board; FE, Fixed-Effects; IV, Intrumental Variables; TLAC, Total-loss-absorbing-capacity; SUR, Seemingly Unrelated Regressions

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Table 1.A.3 Literature: financial stability

Authors	**Type**	**Topics**	**Methodology and conclusions**
Bennani et al. (2017)	Book	Macroprudential policy	-
Benoit et al. (2017)	Survey	Systemic Risks	Three origins to systemic risks: systemic risk taking, contagion and amplification
Bussiere and Fratzscher (2006)	Empirical	Early warning indicators	Multinomial logit. Variables: overvaluations, lending boom, growth, current account, short-term debt/reserves, domestic credit, financial interdependence
Drehmann and Juselius (2014)	Empirical	Early warning indicators	Non-parametric. Credit to GDP, debt to service, non-core liability
Dumičić (2016)	Empirical	Financial stability indicator	PCA. 6 groups of variables (15): banks, corporate, households, government, macroeconomic developments, system resilience
Gadanecz and Jayaram (2009)	Survey	Financial stability measures	PCA, CFA, weighted index, cumulative simulation function, variance equal method
IMF, ECB, Fed, BdF, BD'I, RBA	FSR	Stability indicators/sectors of interest	See Table 1.1
Joint Research Centre-European Commission (2008)	Survey	Methodology for composite indicators	Multivariate analysis (among which: PCA), normalisation, weighting methods, aggregation methods, uncertainty and sensitivity analysis

Note: PCA, Principal Component Analysis; CFA, Common factor Analysis; PP, Position Paper; NPL, Non-Performing Loans; CNB, Central National Bank, FSR, Financial Stability Review

Appendix 1.B Financial Stability Indicator: results, technical appendices and robustness discussion

1.B.1 Data description

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Table 1.B.1 Data description

Topic	Variable name	Measure	Comment	Source
• External sector	Openness	Percentage of GDP	Sum of exports and imports of goods and services measured as a share of gross domestic product.	World Bank
• External sector	Current Account (CA)	Percentage of GDP	Sum of net exports of goods and services, net primary income, and net secondary income.	World Bank
• External sector	Real Effective Exchange Rate (REER)	Index based on 2010=100	Weighted average of a country's currency in relation to an index or basket of other major currencies, adjusted for the effect of inflation.	CEPII[30]

[30] EQCHANGE database, Couharde et al. (2018).

Table 1.B.1 (continued)

• External sector	Foreign reserves (FXR)	Level/US dollar		IMF[31]
• Financial sector	Credit to non-financial sector (CredNF)	Percentage of GDP	Collected at the end of period. Adjusted fo breaks.	BIS
• Financial sector	Real Interest Rate (RIR)	Percentage	Interest rate adjusted to remove the effect of inflation.	OECD
• Financial sector	Financial Integration (FI)	Percentage of GDP	Calculated as the sum between total liabilities and total assets in percentage of GDP in local currency (Lane and Milesi-Ferretti (2018) methodology).	IMF
• Financial sector	Non-performing loans to total gross loans (NPL)	Percentage	Value of nonperforming loans divided by the total value of the loan portfolio (including nonperforming loans before the deduction of specific loan-loss provisions).	IMF (GFSR)

[31] Lane and Milesi-Ferretti (2018)'s database

Table 1.B.1 (continued)

• Financial sector	Interbank interest rate (IIR)	Percentage	Gives the level of trust in the interbanking sector	Fed
• Financial sector	Financial Stress (Stress)	Growth rate	Capture local-regional financial stress. CISS for European countries / Fed Saint Louis for US and Canada.	ECB and Fed
• Financial sector	Banks' z-score (Zscore)		It captures the distance to default of a country's commercial banking system.[32]	World Bank
• Financial sector	Volatility Index (VIX)	Percentage	Captures the volatility risk and is supposed to report for financial integration on the European/Japan side.	Fed

[32] Z-score compares the buffer of a country's commercial banking system (capitalization and returns) with the volatility of those returns. It is estimated as $\frac{ROA+\frac{equity}{assets}}{sd(ROA)}$; sd(ROA) is the standard deviation of ROA. ROA, equity, and assets are country-level aggregate figures Calculated from underlying bank-by-bank unconsolidated data from Bankscope.

Table 1.B.1 (continued)

• Financial sector	Treasury-Eurodollar Spread (TEDS)	Percent	Calculated as the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. The series is lagged by one week because the LIBOR series is lagged by one week due to an agreement with the source. In our study we used annual average.	Fed
• Financial sector	House Prices (HP)	Nominal/US dollar	Those data were not satisfying and therefore not retained for the study.	BIS
• Real sector	Growth rate of gross domestic product per capita (GDP)	Growth rate	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars.	World Bank
• Real sector	Inflation (Inf)	Growth rate	Sustainable, general, self-sustaining increase in the prices of goods and services.	World Bank

Table 1.B.1 (continued)

• Real sector	Public Deficit (GovDef)	Percentage of GDP	Fiscal position of government after accounting for capital expenditures.	World Bank
• Real Sector	Broad money M3 (M3)	Index based on 2010=100	Includes currency, deposits with an agreed maturity of up to two years, deposits redeemable at notice of up to three months and repurchase agreements, money market fund shares/units and debt securities up to two years.	OECD
• Real sector	World GDP growth rate per capita (WGDP)	Growth rate	Same variable for every countries	World Bank

Table 1.B.1 (continued)

• Real sector	General government debt (GovDebt)	Percent (GDP)	Amount of a country's total gross government debt as a percentage of its GDP. It is an indicator of an economy's health and a key factor for the sustainability of government finance.	OECD

Note: all variables were found available for the period 2004-2016 except for rare observations. If necessary, we applied a projection on the previous (or next) years of the missing value in order to obtain a completely balanced panel.

1.B.2 Principal component analysis (PCA)

The principle of this multivariate technique is to capture the common variation from a set of variables correlated[33] with each other, and to resituate it in the form of orthogonal variables. Those are called principal components. Therefore, implementing principal component analysis on variables representing commonly financial stability, we intend to extract an indicator of financial stability.[34] Besides, PCA allows us to considerably reduce the number of variables considered. Therefore, it fits our study since we need to account for different sectors and variables through one single indicator.

Overall PCA extracts most information of a dataset, reduces its size and allows for a better interpretation of the panel. To do so, principal components, or factors, are obtained from a singular value decomposition of the original dataset. The procedure computes factors in such a way that the first component is associated to the highest explained variance and higher eigenvalue, the second one corresponds to the second highest variance and eigenvalue, and so on for the other factors.

Several criteria exist to select the number of components to retain. The most common one is Kaiser (n.d.) criterion which advise to drop all factors with eigenvalue below 1. This approach regularly leads to results close to those of the scree plot method (Cattell, 1966) or the elbow method. Typically, researchers retain enough components to explain at least 80 to 90% of the variance.

It is common to perform a rotation after factors' selection. The most popular

[33] See Abdi and Williams (2010).

[34] As we shown it in the literature review, this approach is also recommended in Gadanecz and Jayaram (2009).

method is the *varimax* methodology (Kaiser, n.d.), which considers that components are associated to few large loadings[35] and many small loadings. *Varimax* procedure looks for a linear combination of the original factors maximizing the variance of the loadings.

1.B.3 Correlation analysis

In this subsection, we give insight on our correlation analysis and data selection. We have to deal with an important number of variables since financial stability measurement requires to take into account many sectors. From variables we need to select those which are strongly correlated with each other for all countries.

To this end, we follow a procedure of variable selection based on correlation analysis. First, and for all 20 initial variables, we calculate the correlation matrices. For each of them and for all countries, we associate a new matrix scoring 1 if the correlation for a given variable pair is statistically significant, and 0 if not.[36] Therefore, summing all the new matrices, we have a general symmetric table, a hit map after removing the first variables (see Table 1.B.2) giving for each line i and each raw j ($i \neq j$) the number of times a couple of variables is being statistically significantly correlated among the 23 countries. This approach reveals wich variables are the most correlated with each other for all our panel. Then, we sum for each variable the score it obtained with all the other ones and use this score to conduct our first selection. Using this procedure, we select 12 variables

[35] The loadings are the correlation coefficients between the principal components and the variables, giving contribution of an observation to a component.

[36] The new matrices are also scoring 0 on the diagonal ($corr(X_i; X_i) = 1$).

(GDP, world GDP, M3, government deficit, government debt, TEDS, stress, credit to non-financial institutions, non-performing loans, openness, foreign exchange rate and VIX) and reject the following 8 variables: inflation, Z-score, real interest rate, financial integration, current account, real effective exchange rate, house prices and interbank interest rate.

Table 1.B.2 Hit map after removing lowest correlated variables

	GDP	**WGDP**	**M3**	**GovDef**	**GovDebt**	**TEDS**	**Stress**	**CredNF**	**NPL**	**Openness**	**FXR**	**VIX**
GDP	0											
WGDP	21	0										
M3	0	1	0									
GovDef	11	13	1	0								
GovDebt	15	11	3	7	0							
TEDS	21	23	0	5	9	0						
Stress	0	0	17	3	1	0	0					
CredNF	9	9	2	9	10	6	4	0				
NPL	10	9	1	8	12	6	4	7	0			
Openness	14	20	0	11	3	7	0	2	4	0		
FXR	9	11	1	6	2	4	0	2	4	7	0	
VIX	0	0	16	3	0	0	22	3	4	0	0	0
Total	110	119	43	75	72	83	53	64	71	68	46	48

Source: author's calculations. Interpretation: cell i, j gives the number of times the variable pair (X_i, X_j) is significantly correlated for all 23 countries. For instance: out of 23 countries, there are 21 for which GDP per capita is significantly correlated with world GDP.

Note: in red scores over 8, in yellow scores going from 5 to 7, in light blue scores going from 1 to 4, and in blue scores equal to 0.

As implementing PCA on this set of 12 variables does not lead to conclusive results, we separate the dataset into three sectors. Before conducting the two-steps PCA, we had to verify that variables were still higly correlated inside each sector. We adopt the same approach as described above for each group, and show that the two steps PCA is relevant (see Table 1.B.3).

Table 1.B.3 Subsectors' correlation analysis

Financial sector

	Stress	CredNF	NPL	VIX	M3
Stress	0				
CredNF	4	0			
NPL	6	7	0		
VIX	22	3	4	0	
M3	17	2	2	16	0
Total	49	16	19	45	37

Real sector

	GDP	WGDP	GovDebt	TEDS
GDP	0			
WGDP	20	0		
GovDebt	15	10	0	
TEDS	21	23	8	0
Total	56	53	33	52

External sector

	Openness	FXR	GovDef
Openness	0		
FXR	7	0	
GovDef	11	6	0
Total	18	13	17

Source: author's calculation.

Appendix 1.C Models and descriptive statistics

1.C.1 Models: sub-groups interaction

Here we present the models with interaction effects and quadratic terms for the three subgroups of banks. Models with the orthogonalized interaction variables are referred as (2.2') for GSIBs, (2.3') for DSIBs and (2.4') for others.

- GSIBs:

$$FSI_{i,t} = \alpha_i + \beta_1 GCap_{i,t} + \beta_4 GCenterCap^2_{i,t} + \beta_2 GLiq_{i,t} \\ + \beta_5 GCenterLiq^2_{i,t} + \beta_6 GInterac_{i,t} + \beta_3 GX_{i,t} + \epsilon_{i,t} \tag{2.2}$$

- DSIBs:

$$FSI_{i,t} = \alpha_i + \beta_1 DCap_{i,t} + \beta_4 DCenterCap^2_{i,t} + \beta_2 DLiq_{i,t} \\ + \beta_5 DCenterLiq^2_{i,t} + \beta_6 DInterac_{i,t} + \beta_3 DX_{i,t} + \epsilon_{i,t} \tag{2.3}$$

- Others:

$$FSI_{i,t} = \alpha_i + \beta_1 OCap_{i,t} + \beta_4 OCenterCap^2_{i,t} + \beta_2 OLiq_{i,t} \\ + \beta_5 OCenterLiq^2_{i,t} + \beta_6 OInterac_{i,t} + \beta_3 OX_{i,t} + \epsilon_{i,t} \tag{2.4}$$

where the letters G, D and O are standing respectively for GSIBs, DSIBs and Others. For each sub-group, the model is estimated before and after the orthogonalization process.

The orthogonalized interaction model with quadratic terms in the case of all banks is written as follows:

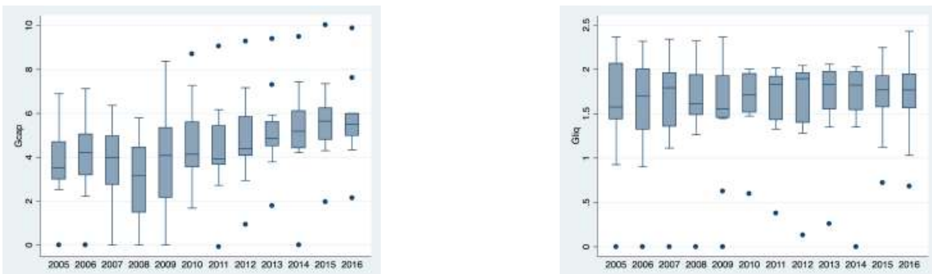
$$FSI_{i,t} = \alpha_i + \beta_1 Cap_{i,t} + \beta_4 (Cap_{i,t} - \bar{Cap}_{i,.})^2 + \beta_2 Liq_{i,t} \\ + \beta_5 (Liq_{i,t} - \bar{Liq}_{i,.})^2 + \beta_6 Interac^{\psi}_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{2.1'}$$

where $Interac^{\psi}$ is the interaction term between capital and liquidity orthogonalized variables. Following Balli and Sorensen's (2013) recommendation: $Interac =$

$Cap^{\psi}Liq^{\psi}$, where $Cap^{\psi} = M_{cap}Cap$ and M_{cap} is the residual from regressing Cap on a constant (and upside down for Liq^{ψ}). $\bar{var}_{i,.}$ refers to the intertemporal mean of each individual, with var denoting the considered variable.

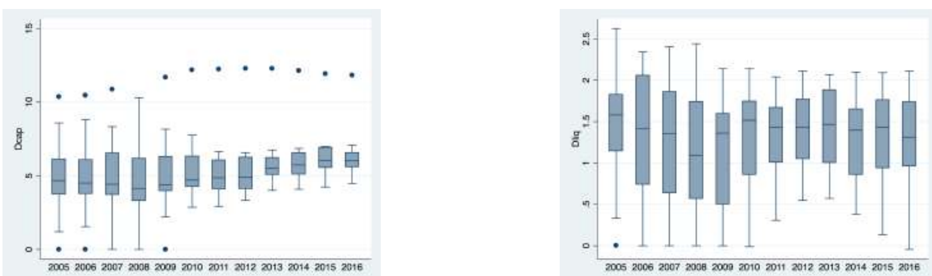
1.C.2 Descriptive statistics

Figure 1.C.1 – Capital and liquidity - GSIBs - FitchConnect



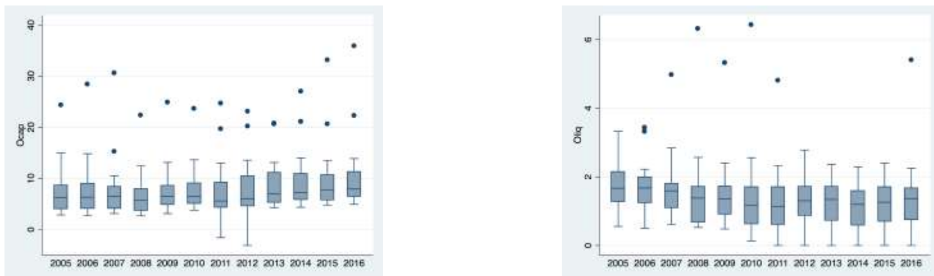
Source: Author's calculations from FitchConnect data.

Figure 1.C.2 – Capital and liquidity - DSIBs - FitchConnect



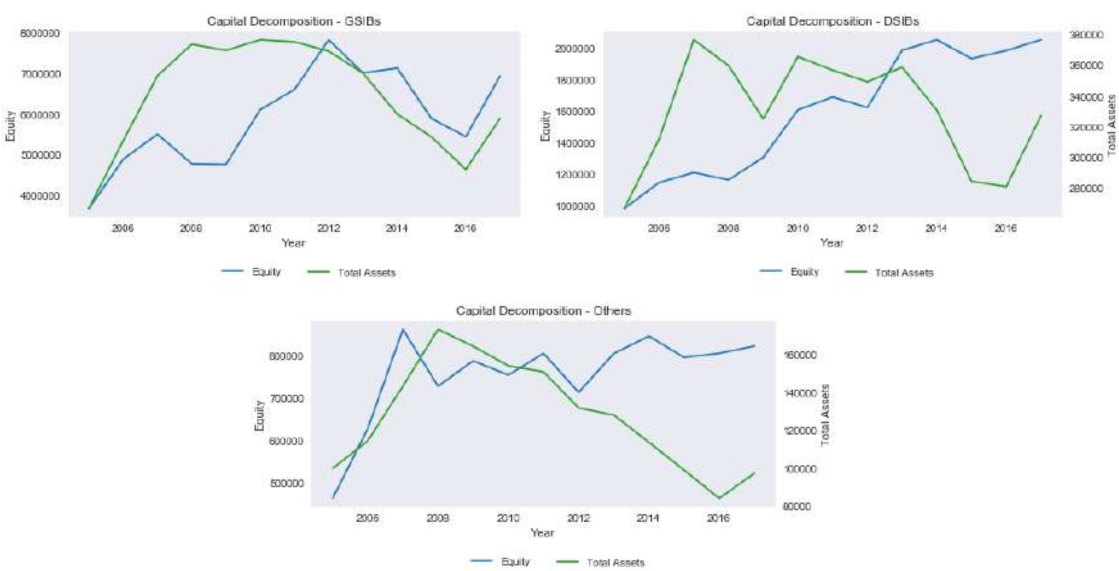
Source: Author's calculations from FitchConnect data.

Figure 1.C.3 – Capital and liquidity - Others - FitchConnect



Source: Author's calculations from FitchConnect data.

Figure 1.C.4 – Breaking down capital proxies - FitchConnect



Source: Author's calculations from FitchConnect data. In blue, Equity, in green, Total Assets

Appendix 1.D Specification tests

1.D.1 Cross-dependence tests

Table 1.D.1 Cross-dependence tests

Models	Before orthogonalization				After orthogonalization			
	Pesaran		Fisher		Pesaran		Fisher	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
(2.1)	4.875	0.0000	28.946	0.1464	4.877	0.0000	30.231	0.1130
(2.2)	-0.815	0.153	7.115	0.7897	-0.613	0.5398	8.269	0.6890
(2.3)	-0.910	0.3627	5.974	0.8751	-0.835	0.4035	7.987	0.7145
(2.4)	5.089	0.0000	30.926	0.0976	4.828	0.0000	29.468	0.1320

Source: Author's calculations.

1.D.2 Unit root tests

Table 1.D.2 Harris and Tzavalis test

Variable	Models			
	(1.2)		(1.3)	
	Statistic	P-Value	Statistic	P-Value
FSI2007	0.600	0.008	0.600	0.008
Capital	0.770	0.506	0.826	0.799
Liquidity	0.757	0.431	0.658	0.051
Profitablity	0.374	0.000	0.410	0.000
Loan	0.509	0.001	0.797	0.659
IIR	0.781	0.567	0.781	0.567
Zscore	0.693	0.141	0.693	0.141
Inflation	0.269	0.000	0.269	0.000

Source: Author's calculations.

The CIPS (Pesaran, 2007) test statistic is calculated as a Cross-sectional Augmented Dickey-Fuller (CADF) average. In the same way as for a conventional ADF test, under the null hypothesis, the series has at least one single root and is not stationary. The test is divided into three models: (a), the model with constant and trend; (b), the model with constant without trend; and (c), the model without constant and trend. The critical values of the CIPS test are as follows: model (a) -2.66 at the 10% threshold, -2.76 at the 5% threshold and -2.93 at the 1% threshold; model (b) -2.14 at the 10% threshold, -2.25 at the 5% threshold and -2.44 at the 1% threshold; model (c) -1.52 at the 10% threshold, -1.64 at the 5% threshold and -1.86 at the 1% threshold.

Table 1.D.3 CIPS test

Variables	Test models	Regression models	
		(1.1)	(1.4)
Capital	a	-2.312	-2.474
	b	-1.424	-1.507
	c	-1.374	-1.458
Liquidity	a	-2.270	-2.391
	b	-1.980	-2.439
	c	-1.861	-1.897
Profitability	a	-2.410	-2.775
	b	-2.368	-2.590
	c	-1.338	-1.411
Loan	a	-2.860	-2.714
	b	-1.491	-1.808
	c	-1.110	-1.368
IIR	a	-1.700	-1.700
	b	-1.343	-1.343
	c	-1.231	-1.231
Zscore	a	-2.319	-2.319
	b	-1.597	-1.597
	c	-1.343	-1.343
Inflation	a	-2.178	-2.178
	b	-2.310	-2.310
	c	-2.125	-2.125

Source: Author's calculations.

1.D.3 Hausman test

Table 1.D.4 Hausman test

Models	(2.1)	(2.2)	(2.3)	(2.4)
Statistic	7.01	34.14	80.62	6.12
P-Value	0.7246	0.0002	0.0000	0.8052

Source: Author's calculations.

Appendix 1.E PSTR

1.E.1 Results - Homogeneity and nonlinearity tests

Table 1.E.1 Results - Homogeneity tests

Transition Variable: Capital							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(18,213)	2.349	0.002	Chi2(18)	80.927	0.000
GSIBs	$H_{03} : \beta_3 = 0$	F(6,213)	2.440	0.026	Chi2(6)	39.899	0.000
	$H_{02} : \beta_2 = 0 \vert \beta_3 = 0$	F(6,219)	1.433	0.202	Chi2(6)	10.591	0.101
	$H_{01} : \beta_1 = 0 \vert \beta_2 = \beta_3 = 0$	F(6,225)	2.966	0.008	Chi2(6)	28.091	0.000
(3.3)	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(12,219)	2.533	0.003	Chi2(12)	52.236	0.000
DSIBs	$H_{03} : \beta_3 = 0$	F(4,219)	1.427	0.225	Chi2(4)	9.771	0.044
	$H_{02} : \beta_2 = 0 \vert \beta_3 = 0$	F(4,223)	2.370	0.053	Chi2(4)	13.735	0.008
	$H_{01} : \beta_1 = 0 \vert \beta_2 = \beta_3 = 0$	F(4,227)	3.667	0.006	Chi2(4)	20.004	0.000

Source: Author's calculations.

Table 1.E.2 Test of Linearity vs PSTR

Transition Variable: Capital								
Model	m	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	1	$H_0 : \beta_1 = 0$	F(6,225)	2.966	0.008	Chi2(6)	28.091	0.000
(3.3)	1	$H_0 : \beta_1 = 0$	F(4,227)	3.667	0.006	Chi2(4)	20.004	0.000

Source: Author's calculations. Note: m is the number of threshold selected by the model.
β_1 is the vector of parameters for variables associated with the transition function

Table 1.E.3 Results - Homogeneity tests

Transition Variable: Liquidity							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2')	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(18,213)	1.622	0.056	Chi2(18)	59.849	0.000
GSIBs	$H_{03} : \beta_3 = 0$	F(6,213)	0.851	0.531	Chi2(6)	8.879	0.180
	$H_{02} : \beta_2 = 0 \vert \beta_3 = 0$	F(6,219)	2.043	0.061	Chi2(6)	22.762	0.000
	$H_{01} : \beta_1 = 0 \vert \beta_2 = \beta_3 = 0$	F(6,225)	1.934	0.076	Chi2(6)	23.160	0.000
(3.3')	H_0: $\beta_1 = \beta_2 = \beta_3 = 0$	F(12,219)	4.072	0.000	Chi2(12)	120.471	0.000
DSIBs	$H_{03} : \beta_3 = 0$	F(4,219)	4.741	0.001	Chi2(4)	50.423	0.000
	$H_{02} : \beta_2 = 0 \vert \beta_3 = 0$	F(4,223)	3.355	0.010	Chi2(4)	26.967	0.000
	$H_{01} : \beta_1 = 0 \vert \beta_2 = \beta_3 = 0$	F(4,227)	3.504	0.008	Chi2(4)	22.389	0.000

Source: Author's calculations.

Table 1.E.4 Test of Linearity vs PSTR

Transition Variable: Liquidity								
Model	m	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2')	1	$H_0 : \beta_1 = 0$	F(6,225)	1.934	0.076	Chi2(6)	23.160	0.000
(3.3')	1	$H_0 : \beta_1 = 0$	F(4,227)	3.504	0.008	Chi2(4)	22.389	0.000

Source: Author's calculations. Note: m is the number of threshold selected by the model.
β_1 is the vector of parameters for variables associated with the transition function

1.E.2 Results - Constancy and no remaining heterogeneity tests

Table 1.E.5 No-remaining heterogeneity tests and constancy

Model	Hypothesis	Test	Value	SL	Robust	Value	SL
Test of no remaining heterogeneity							
$H_0' : G_2 = 0$							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	$\gamma_2 = 0 \vert m = 2$, adding GCAP	F(12,213)	1.388	0.172	Chi2(12)	32.335	0.001
	$\gamma_2 = 0 \vert m = 1$, adding GCAP	F(6,219)	1.880	0.085	Chi2(6)	18.558	0.004
(3.2')	$\gamma_2 = 0 \vert m = 2$, adding GLIQ	F(12,213)	1.398	0.168	Chi2(12)	31.714	0.001
	$\gamma_2 = 0 \vert m = 1$, adding GLIQ	F(6,219)	1.638	0.137	Chi2(6)	20.067	0.002
(3.3)	$\gamma_2 = 0 \vert m = 2$, adding DCAP	F(8,219)	1.090	0.370	Chi2(8)	14.407	0.071
	$\gamma_2 = 0 \vert m = 1$, adding DACP	F(4,223)	1.363	0.247	Chi2(4)	8.965	0.061
(3.3')	$\gamma_2 = 0 \vert m = 2$, adding DLIQ	F(8,219)	2.444	0.014	Chi2(8)	49.796	0.000
	$\gamma_2 = 0 \vert m = 1$, adding DLIQ	F(4,223)	3.618	0.007	Chi2(4)	30.930	0.000
. Test of parameter constancy							
$H_0' : G_2 = 0$							
Model	Hypothesis	Test	Value	SL	Robust	Value	SL
(3.2)	$\gamma_2 = 0 \vert m = 2$, adding (t/T)	F(24,201)	2.687	0.000	Chi2(24)	117.502	0.000
	$\gamma_2 = 0 \vert m = 1$, adding (t/T)	F(12,213)	1.869	0.039	Chi2(12)	56.931	0.000
(3.2')	$\gamma_2 = 0 \vert m = 2$, adding (t/T)	F(24,201)	1.925	0.008	Chi2(24)	93.182	0.000
	$\gamma_2 = 0 \vert m = 1$, adding (t/T)	F(12,213)	1.355	0.189	Chi2(12)	27.437	0.006
(3.3)	$\gamma_2 = 0 \vert m = 2$, adding (t/T)	F(16,211)	2.471	0.001	Chi2(16)	101.851	0.000
	$\gamma_2 = 0 \vert m = 1$, adding (t/T)	F(8,219)	2.107	0.036	Chi2(8)	38.498	0.000
(3.3')	$\gamma_2 = 0 \vert m = 2$, adding (t/T)	F(16,211)	3.027	0.000	Chi2(16)	101.443	0.000
	$\gamma_2 = 0 \vert m = 1$, adding (t/T)	F(8,219)	2.359	0.018	Chi2(8)	32.719	0.000

Source: Author's calculations.

Chapitre 2

What do bankruptcy prediction models tell us about banking regulation? Evidence from statistical and intelligent approaches[†]

[†]Je souhaiterais particulièrement remercier Valérie Mignon pour ses conseils et remarques. Je tiens également à remercier grandement Gaëtan Le Quang avec qui ce chapitre a été co-écrit. Nous avons su trouver une efficace et pertinente complémentarité.

2.1 Introduction

Bankruptcy prediction is a constantly growing field of research. Starting with the seminal paper by Altman (1968) that identified several key ratios to predict firms' bankruptcy, the literature has evolved both by diversifying the type of firms considered and by proposing increasingly complex methods. The main interest associated with developing good bankruptcy prediction models is to offer a way to monitor the soundness of a given firm in real time. Another interest is to provide a ground to regulatory constraints. This is of particular interest as far as banks are concerned.

Banking regulators indeed need to know what are the main predictors of banks' default to design rules meant to prevent such default from happening. The purpose of this chapter is to discuss current banking regulation in the light of what bankruptcy prediction models tell us about the main determinants of banks' failure. To do so, we resort both (i) to a standard statistical approach by estimating a logistic regression (logit) on data covering both US and European banks, and (ii) to more sophisticated intelligent approaches by presenting results coming from random forest classifications (RF) and from artificial neural networks (ANN). Overall, we find that capital outperforms other balance sheet variables in predicting bankruptcy. In addition, the complex Basel capital ratio does not outperform the simple leverage ratio in predicting banks' default, which forces to question the rationale behind the former. As for liquid assets holding, our models suggest that banks that hold a great amount of liquid assets go more frequently bankrupt than banks investing in less liquid assets. Our models perform well on the US database, but exhibit low performances on European data.

Banking regulation is currently implemented through several rules whose main purpose is to ensure both the soundness of the banking system as a whole (macro-prudential rules) and of each bank individually (micro-prudential rules). Banking regulation was traditionally implemented through a capital ratio whose purpose was to ensure a loss-absorbing capacity on the liability side of the balance sheet. To better take into account the risk taken on the asset side of the balance sheet, this ratio has progressively evolved toward a risk-based ratio, meaning that capital requirements are computed as a function of the risk-weighted assets (RWA). Given the complexity of banks' activities, computing the RWA is not trivial and regulators often lack information or expertise to assess the risk associated with each individual bank. As a consequence, under certain conditions, banks are allowed to resort to internal models, through what the regulatory framework referred to as the advanced internal ratings-based approach (A-IRB), to assess the risk associated with their portfolio of assets. Such internal computations of RWA have however been shown to underestimate the risk associated with banks' activities (Mariathasan and Merrouche, 2014).

After the 2007-2008 crisis, banking regulators added liquidity ratios to the risk-weighted capital ratio. The necessity of liquidity regulation is grounded on the illiquidity spirals that materialized during the crisis and led to the collapse of the banking system (Brunnermeier and Pedersen, 2009). Liquidity regulation has been implemented through two different rules: the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The LCR states that banks need to hold enough high quality liquid assets (HQLA) to withstand a liquidity crisis lasting 30 days. The NSFR states that banks' illiquid assets need to be funded through stable funding instruments. Having a closer look at the two ratios, we notice that they are in fact redundant (Bolton et al., 2019). Instead of two ratios, liquidity regulation would thus be better off defining only one ratio. Which ratio should then be ruled out and which should remain? We believe that the perspective that should be adopted is that of the NSFR. Our models indeed suggest that liquid assets holding could actually increase the probability that banks go bankrupt. If liquid assets allow banks to face short-term liquidity needs, they are nonetheless often associated with low returns that could explain why in some cases banks that hold a great proportion of their asset portfolio in liquid assets go more frequently bankrupt than other banks.

From this quick overview of our results and of banking regulation, we formulate policy recommendations. Specifically, we think that banking regulation would be better off focusing on equity to ensure the soundness of the banking system. As can indeed be theoretically shown (see Appendix 2.A), equity outperforms liquid assets in preventing a bank from defaulting even when the return associated with those assets is not lower than the return demanded by the creditors of the bank (i.e. even when liquid assets holding is assumed to have a negative impact on the probability of default). In addition, we argue that the simple leverage ratio should be preferred to the sophisticated Basel one. Our results indeed suggest that the latter does not outperform the former at predicting banks' failure, while this latter is far more difficult to compute than this former. Equity should thus be preferred to more complex definitions of capital. Moreover, as shown in Durand and Le Quang (2020), increasing equity requirements has a positive impact on banks' profitability when measured as the ROA. Since the ROA is by far the main predictor of bankruptcy, increasing equity requirements would probably lower the occurrence of defaults through two channels: the direct channel of capital (increase in the loss-absorbing capacity of the liability side of the balance sheet), and the indirect channel of the ROA (increase in the return associated with the asset side of the balance sheet).

This paper is in line with the literature through the use and comparison of traditional and more recent classification methods. It is quite conventional, on this type of issue, to propose a comparison of the models and their respective performances. We have therefore come here to expand the literature, by basing ourselves on some of the models identified as the most efficient for this subject, and by proposing to focus on the role of banking regulation in determining bank default. The study of the European case also constitutes an innovation in the literature, since the emphasis is generally done on the US case. Finally, our investigation gives keys to understand regulatory efficiency and complexity issue.

The rest of the chapter is organized as follows. The next section reviews the literature on bankruptcy prediction models. Section 2.3 offers some details on the models we use. Section 2.4 describes our database. Section 2.5 presents the main results. Robustness checks are provided in Section 2.6, and Section 2.7 concludes.

2.2 Literature review

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 inconvenient to delete potentially interesting 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 (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). Given our database, we therefore resort to SMOTE to balance our dataset.

Once the dataset re-sampled, 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 (Ohlson, 1980; Jones and Hensher, 2004) and for banks (Martin, 1977; Kolari et al., 2002). Intelligent methods consist in machine learning techniques such as neural network or random forest. Specifically, neural network is largely used in the bankruptcy prediction literature (Ravi Kumar and Ravi, 2007) and is often shown to perform better than logistic regressions (Tam and Kiang, 1990; Tam, 1991; Salchenberger et al., 1992). Fewer papers resort to random forest regressions to predict firms' failures (Zoričák et al., 2020).

The literature on bankruptcy prediction 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). Capital adequacy, Assets quality, Management, Earnings, Liquidity, and Sensitivity (CAMELS)[1] ratings are also based on the main results found in the literature on bankruptcy prediction. Ravi Kumar and Ravi (2007) provide an exhaustive review of the variables found as predictors of banks' bankruptcy in papers published from 1968 to 2005.

[1]CAMELS constitutes the six factors used by regulatory authorities to classify financial institutions in function of their quality.

2.3 Methodology

As discussed above, in order to assess the importance of capital and equity ratios on banks' default probability, we rely on three classification methods. For all of those approaches, the objective is to estimate the function f, on which we have no *a priori*, that defines the true model: $P(y = \{0,1\}|X = x) = f(x) + \epsilon$, where $P(y = \{0,1\}|X = x)$ is the probability that y, the explained variable, equals 1 or 0, y takes the value 1 at time $t-1$ for banks that fail in t and 0 otherwise, x refers to the explanatory variables and ϵ designates the error term.

The major issue in our empirical approach is the sparsity of the Y matrix. To avoid this problem we use the Synthetic Minority Oversampling Technique (SMOTE). We describe this procedure and give an overview of our methodologies and interpretation techniques. For the sake of clarity, we give only brief insight on our methodology, and refer the reader to Appendix 2.C for more details.

Synthetic Minority Oversampling Technique (SMOTE)

As said earlier, we consider methods associated with extreme rare events to tackle our deeply imbalanced database: SMOTE (Chawla et al., 2002). As a robustness check and for transparency matters, we give class weight results in Section 2.6.

SMOTE uses the k nearest neighbors of all minority class examples to synthesize new minority class instances: synthetic observations are created on the line between the existing ones. The recourse to nearest neighbors ensures to replicate the distribution of the original data. In order to avoid over-fitting issues, the SMOTE procedure is only applied on the training sample. The test sample remains imbalanced.

Logistic regression

Logistic regression model (Hastie et al., 2009) comes from the wish to assess the probability of classes as a linear function of explanatory variables while respecting that the sum of probabilities equals 1. In a binary class model, it takes the following form:

$$log\frac{P(y=0|X=x)}{P(y=1|X=x)} = \beta_0 + \beta_1^T x \qquad (2.1')$$

where β_0 is the intercept included in the model and β_1^T stands for the vector of parameters. After rearrangement, we obtain:

$$\begin{cases} P(y=1|X=x) = \frac{1}{1+exp(\beta_0+\beta_1^T x)} \\ P(y=0|X=x) = 1 - \frac{1}{1+exp(\beta_0+\beta_1^T x)} \end{cases}$$

It is widely accepted that in a matter of logit interpretation, one has to refer to the odds ratio ($OR(x_j)$) which is calculated as the exponential of the coefficient associated with an explanatory variable. It is interpreted as follows: all things being equal, an increase of one unit in variable j induces a change in the probability of class 1 by a factor of $OR(x_j)$.

Random forest (RF)

Random forest classification (Breiman, 2001) consists in averaging a more or less large number of decision trees. A tree is built *via* recursive binary partition of the explanatory variables, or features, spaced into M final regions. At every step, or node, the best splitting point is computed for each feature and the model retains the variable that minimizes the loss function. Once the tree is built, the estimated probability $\hat{p}_{1m}$ of default in region m is given by the proportion of default in the region:

$$\hat{p}_{1m} = \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i = 1) \tag{2.1'}$$

where N_m is the cardinal of region m, m is the region with $m \in [\![1; M]\!]$, $I(y_i = 1)$ is the function that scores 1 if y_i equals 1 and 0 otherwise.

In order to avoid over fitting issues, but to improve the out-of-sample prediction of the model, there are two parameters to optimize at the trees' level and one at the forest's one: the number of final observations per leave (*i.e.*, per final partition space), the number of splits (*i.e.*, the depth of trees), and the number of trees in the forest. To set those hyperparameters, we run numerous estimations and selected those that give the best out-of-sample score.[2]

[2]In this particular context, the score we use is the true positive rate: the number of banks identified as default banks (true positive) over the sum of true positive, and the number of banks identified as not having defaulted while they have. This ratio is called sensitivity.

Artificial neural network (ANN)

Artificial neural networks (McCulloch and Pitts, 1943; Hastie et al., 2009) model links between features and explained variables, or label, through the application and composition of non-linear functions. For complexity matters, we recourse here to the most widely used neural network, called the single hidden layer back-propagation network. It means that we use only one hidden layer between the inputs and the output:

$$
\begin{aligned}
Z_m &= \sigma(\alpha_{0h} + \alpha_h^T X),\, h \in [\![1, H]\!] \\
T_k &= \beta_{0k} + \beta_k^T Z,\, k \in \{0, 1\} \\
f_k(X) &= g_k(T),\, k \in \{0, 1\}
\end{aligned}
\tag{2.1'}
$$

where $\sigma(.)$ is the simoid function given by $\sigma(v) = \frac{1}{1+e^{-v}}$, H is the number of hidden units in the hidden layer, and $g_k(.)$ is the softmax function given by $g_k(T) = \frac{e^{T_k}}{\sum_{l \in \{0,1\}} e^{T_l}}$. Z_m are called hidden units and form the hidden layer because they are not directly observed. ANN have three hyperparameters to be set: the number of hidden layers, the number of hidden units and the batch size.[3] As for RF, to determine those parameters, we select those that maximize the proportion of default banks identified as so among all of those.

[3]It corresponds to the number of observations took to fit the model at each iteration.

Interpretation

An important part of the empirical strategy resides in our capacity to evaluate models' performance, features' significance (or importance), and features' marginal impact on the estimated probability of default. Our objective is to obtain efficient models in their ability to identify default. Then, we look into the role played by equity and capital ratios in the determination of default's probability. Finally, we assess the marginal impact of those ratios on the output. To this aim, we use several performance scores and interpretation tools.

In order to assess the performance of our models, we rely on the confusion matrix (Hand, David, 2012), which is widely used in classification studies. In binary classification problems, confusion matrix gives four elements: the number of true positive (TP, failed banks identified as failed banks), the number of true negative (TN, unfailed banks identified as so), the number of false positive (FP, unfailed banks identified as failed ones), and the number of false negative (FN, failed banks identified as unfailed ones). From those quantities, we can compute some performance scores:[4]

- Mean score of the model: $\frac{TP+TN}{TP+TN+FP+FN}$
- True positive rate (TPR, also called sensitivity or recall): $\frac{TP}{TP+FN}$.
- True negative rate (TNR, or specificity): $\frac{TN}{TN+FP}$
- Positive predictive value (PPV, or precision): $\frac{TP}{TP+FP}$

[4] All those scores are computed in and out-of-sample. We favor the out-of-sample score.

Since the TPR gives the proportion of failed banks identified as so among all failed banks, this is the ratio[5] we are looking to maximize in the hyperparameterization of our model. Indeed, it is far more important for us to identify default banks, even if it increases the false negative rate. We believe that the cost of identifying a bank as not defaulting while it is, is greater than identifying a bank as defaulting while it is not.

In order to evaluate the performance of our models, we rely on conventional measures in binary classification:

- The receiver operating characteristic (ROC), that plots the true positive rate against the false positive rate for different levels of differentiation threshold. This curve allows us to calculate the area under the ROC curve (AUROC) that gives the probability that the classifier ranks a positive randomly selected instance higher than a negative one. Therefore, the AUCROC should be maximized.

- The precision recall curve (PR) that plots the true positive rate against the positive predictive value for a set of different thresholds. The area under the PR (AUPR) should also be maximized even if it has not intuitive interpretation as the AUROC.

The next step is to assess the statistical significance, or importance, of independent variables. Logistic regression being a parametric model, it provides a Z-score, a p-value and a confidence interval. It is not the case for RF and ANN

[5]We maximize the TPR calculated with out-of-sample data.

classifiers. Therefore, we resort to interpretable machine learning tools in order to assess features' importance in determining the output. The independent variables' importance in random forests is assessed given by a generalization of Breiman et al. (1984)'s calculation of relevance in classification trees that measures the improvement made in each node of a tree for each predictor.

However, this measure is specific to RF and decision trees, so we rely on permutation feature importance (Breiman, 2001) for artificial neural networks. This measure attributes to each independent variable a score allowing to order them in function of their importance in determining the output. For a given variable j, it is computed as follows:

1. We calculate the model's score S
2. Then, the variable j is shuffled N times
3. The mean of scores s_n^j given by the model using the shuffled variable is then calculated:
$$S_{mean}^j = \frac{1}{N} \sum_{n \in [\![1,N]\!]} s_n^j$$
4. The importance of the variable j is given by the difference $Imp_j = S - S_{mean}^j$. Therefore, the larger this difference, the more important we can consider the variable to be in the predictive capacity of the model.

Since this permutation feature importance can be assessed for any model that gives prediction, we also computed it for the logistic regression.

As for the marginal impact of features on default probability for non-parametric

RF and ANN models, we rely on two quantitative input influence measures: Partial Dependence Plots (PDP, Friedman (2000), Hastie et al. (2009)) that assess the variations of the output when making one feature varying, and Accumulated Local Effect (ALE, Datta et al. (2016)) that is based on the same logic as PDPs but being computed on variables definition's space and supposed to take into account the potential correlations between independent variables.

2.4 Data and descriptive statistics

2.4.1 Data

Our sample consists in US and European[6] bank's balance sheet variables[7] on the 2000-2018 period extracted from the FitchConnect database. In order to capture the specific information of each variables, we checked their correlations with banks' size measured by total assets. We therefore reported size to variables highly correlated with it. In order to attenuate outliers' effect, we applied a log transformation to variables displaying extreme values away from the mean by several tens of times the standard deviation.

After data treatment for missing values, we managed to keep 24 variables, 4707 banks in US among which 454 have defaulted and 3529 European banks among which 205 defaults. Table 2.4.1 below displays the evolution of the number of banks and defaults per year in the two samples.

[6] We consider 12 European countries: Austria, Belgium, Cayman Islands, Denmark, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Spain, United Kingdom. We selected those countries based on the number of defaults per country.

[7] Details on the variables' definition are given in Table 2.B.

Table 2.4.1 Evolution of observations and defaults per year

Year	US			Europe		
	Nb. obs.	Nb. defaults	% default	Nb. obs.	Nb. defaults	% default
2000	3866	0	0.00	353	8	2.27
2001	3961	1	0.03	865	9	1.04
2002	4029	1	0.02	275	2	0.73
2003	4067	3	0.07	272	7	2.57
2004	4076	0	0.00	257	3	1.17
2005	4305	0	0.00	185	0	0.00
2006	4337	1	0.02	197	2	1.02
2007	4435	18	0.41	728	16	2.2
2008	4516	115	2.55	1275	4	0.31
2009	4465	138	3.09	1409	10	0.71
2010	4361	80	1.83	1470	18	1.22
2011	4291	42	0.98	1545	20	1.29
2012	4226	21	0.50	1754	15	0.86
2013	4207	13	0.31	1777	31	1.74
2014	4194	7	0.17	2209	45	2.04
2015	4198	5	0.12	2234	13	0.58
2016	4191	6	0.14	1716	2	0.12
2017	4196	0	0.00	1659	0	0.00
2018	4197	3	0.07	1376	0	0.00

Source: Authors' calculations. The number of defaults refers to the following year.

Failed banks are identified using the Federal Deposit Corporation's (FDIC) list of failed banks[8] for the US sample. There is no such official list for European banks. Therefore, we used the FitchConnect variable identifying closed banks, withdrawing those that are closed because of merger or acquisition. We believe that taking into account balance sheet variables of the year of default to identify default is not relevant for two reasons: (i) it might be too easy to classify failed from unfailed banks since it is likely that some variables take abnormal values during the year of default, and (ii) it is far more interesting to be able to predict default at least one year before its occurrence. In particular, we aim at assessing the role played by regulatory requirements on the probability of default. Therefore, we consider

[8]The US FDIC offers a public list of US banks that have failed since October 1, 2000.

that the incentive to increase certain balance sheet variables is effective when it improves a bank's resilience or, in other words, when it reduces the probability of default. For those reasons, the default dummy has been shifted by one year before its occurrence.

In the following, we draw several remarks on our European sample. As can be seen from Table 2.4.1, the evolution of the number of banks between 2000 and 2008 does not seem to reflect reality. For the sake of comparison with US results, we consider the whole period for the results presented in Section 2.5.2. However, we check for a potential data selection bias, running the models for the European sample on the sub-period 2008-2018 and display the results of this robustness check in Section 2.6.

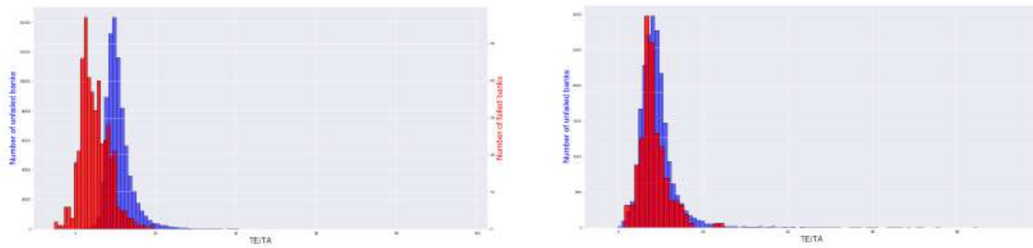
2.4.2 Descriptive statistics

Equity and capital distribution: failed versus unfailed banks

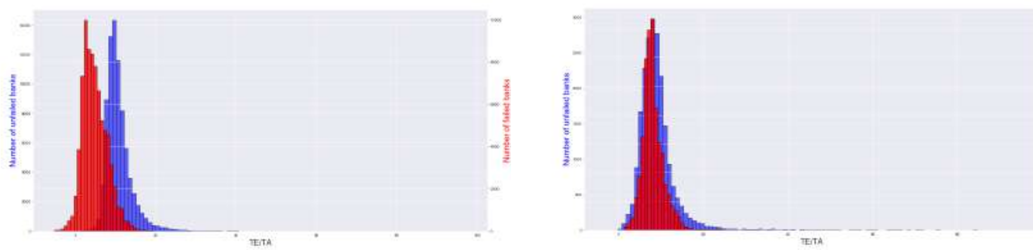
The goal of our models is to classify failed banks aside from unfailed banks. Therefore, we first look into our main variables' distribution separating default from no default in order to reveal eventual differences. Figure 2.4.1 shows TE (Total Equity)/TA (Total Assets) distribution for US and European banks.

Figure 2.4.1 – TE/TA distribution - US versus Europe

(a) Before SMOTE



(b) After SMOTE



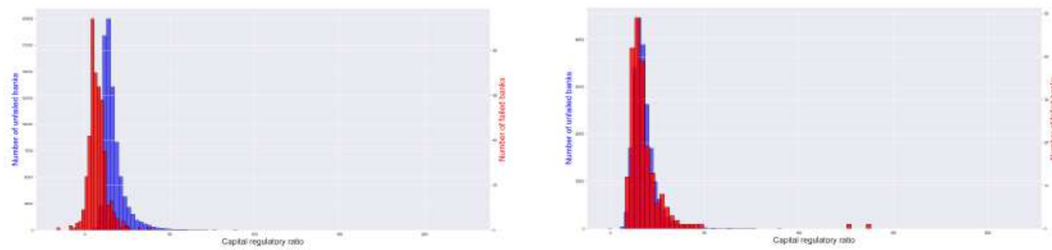
Source: Authors' calculations. Total equity over total assets distribution before and after applying SMOTE on data. The US sample is displayed on the right, the European one on the left.

As can be seen, in the case of the US sample, failed banks are characterized by a lower leverage ratio in the year before default than unfailed banks. The same remark cannot be made regarding the European sample: the distribution of TE/TA is indeed quite similar for failed and unfailed banks. Therefore, we can expect that TE/TA will be a relevant determinant of US banks' default probability, but not for European banks. Besides we should expect a negative impact of this variable on default probability. We can also remark that the distribution seems to keep its characteristics after SMOTE application on data.

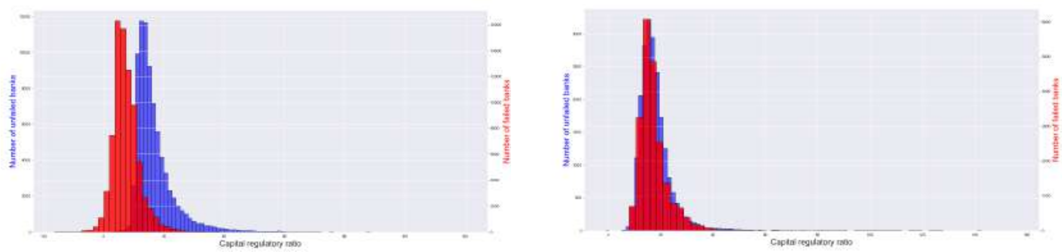
The same remarks can be made on regulatory capital ratio's distribution, as shown in Figure 2.4.2: (i) it appears to be determinant in the US sample, with negative impact on default's probability, (ii) it has almost the same distribution for failed and unfailed banks in the case of European banks, and (iii) SMOTE application to data does not interfere with variables' distributions.

Figure 2.4.2 – Regulatory capital ratio distribution - US versus Europe

(a) Before SMOTE



(b) After SMOTE



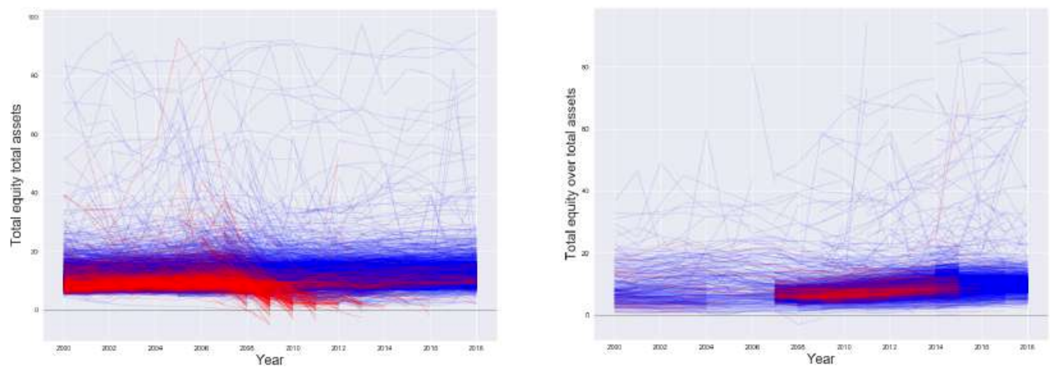
Source: Authors' calculations. Regulatory capital ratio distribution before and after applying SMOTE on data. The US sample is displayed on the right, the European one on the left.

Equity and capital evolution: failed versus unfailed banks

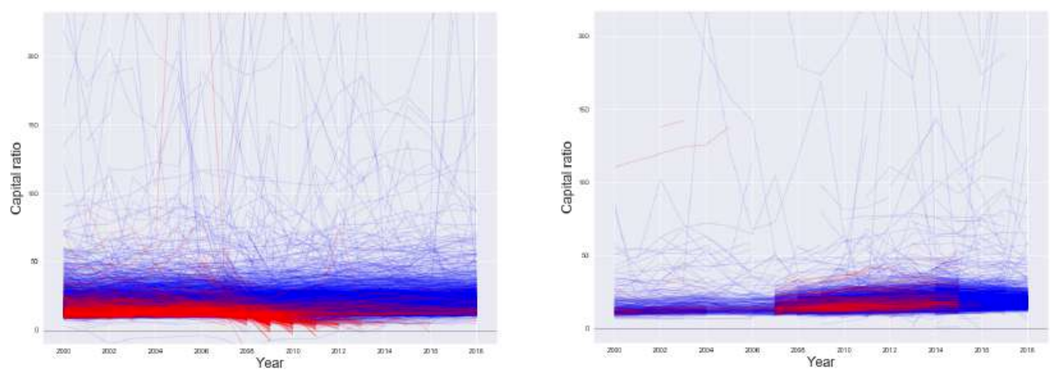
In order to control for potential dynamic effect from independent variables on default probability, we look into our main variables' evolution in Figure 2.4.3.

Figure 2.4.3 – Equity and capital ratios evolution in time - US versus Europe

(a) TE/TA



(b) Regulatory capital ratio



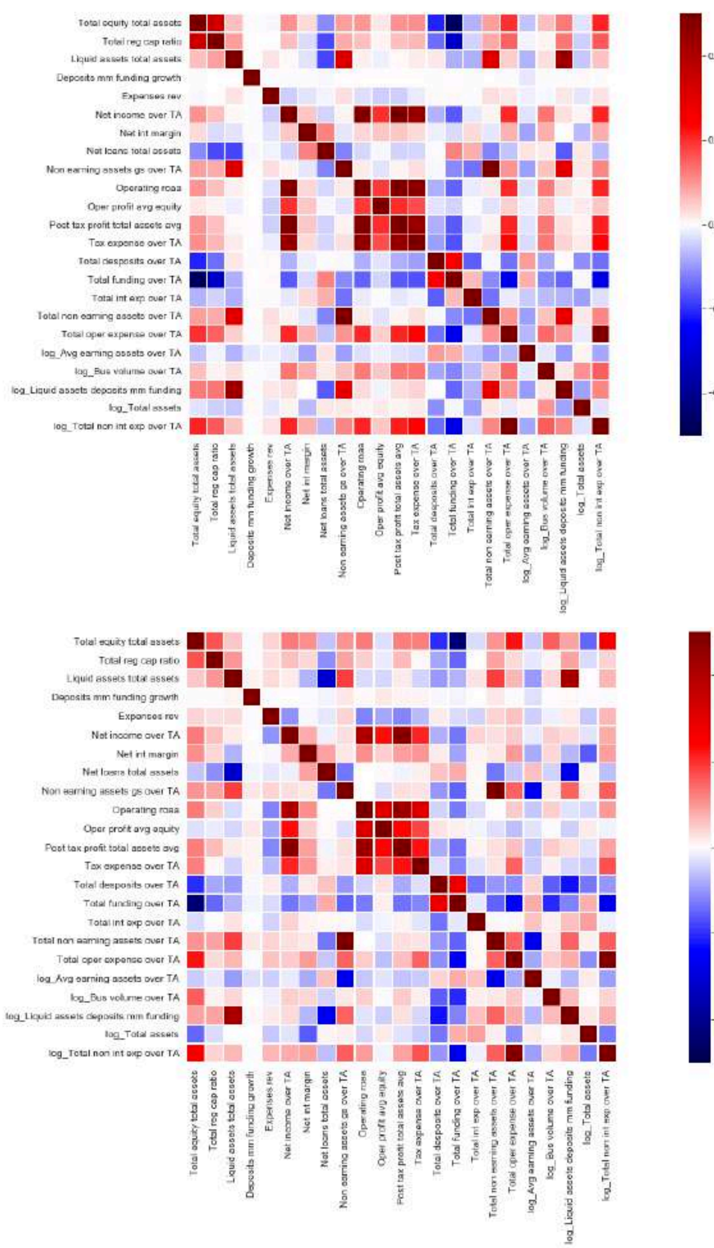
Source: Authors' calculations. TE/TA and regulatory capital ratio distributions. US sample is displayed on the right, European one on the left. Unfailed banks are displayed in blue, failed ones in red.

As can be seen, at least for equity and capital ratios in US, there is a decrease in the two to three years prior to the default. This dynamic, once again, is not observed for European banks. Those observations confirm those we made based on variables' distributions, and show that taking into account temporal dynamic can help to better capture the different balance sheet's characteristics between failed and unfailed banks. To account for this remark, Section 2.6 offers a robustness check in which a time dimension is included in the models.

Variables correlations

The logistic regression does not handle multicolinearity, and Partial Dependence Plots (PDPs) can be biased when independent variables are highly correlated with each other. Figure 2.4.4 shows correlation hitmaps for both samples.

Figure 2.4.4 – Correlation hitmap - US versus Europe



Source: Authors' calculations. The US sample is displayed at the top, the European one at the bottom.

As can be seen, some variables display quite important correlation coefficients with each other. To avoid any bias in our estimations we remove the variables showing high correlation with multiple other features and that could potentially contain quite similar information.[9] Numerous variables remain in our models. This could especially be problematic for the logistic regression that is not built to handle important number of features. As it will be discussed thereafter, we removed variables associated with explosive coefficients from the logistic regression. Regarding PDPs, the use of Accumulated Local Effects (ALE) should ensure the stability of our results.

2.5 Results

2.5.1 US banks

We begin by presenting results for US banks. To do so, we first present the performance of our different models at correctly sorting banks. We then rank variables (features) according to their importance in predicting banks' default. We finally inquire the impact of each significant feature on the probability of default.

2.5.1.1 Models' performance

To study the performance of our models, we resort to the performance measures presented in the methodological section. We focus in particular on the true positive rate (TPR). Recall that this rate measures the proportion of bankrupted banks

[9]Precisely, we removed three variables: Net income over Total Assets, Operating profit avg equity, and Post tax profit total assets avg.

that models identified correctly as bankrupted. Table 2.5.1 presents the value of different performance measures for our three models. We notice that all three models perform well in predicting out-of-sample defaults, with ANN performing better than both Logit and RF. However, ANN seems to under-perform when it comes to identifying non-bankrupted banks. In general, the different performance measures presented indicate that all three models perform well in classifying banks.

Table 2.5.1 Models' performance - US

Scores	Logit		RF		ANN	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Score	90.67	94.95	93.35	**96.59**	90.50	87.63
TPR	86.36	85.37	89.95	86.18	92.99	**91.06**
TNR	95.0	95.0	96.75	**96.64**	88.03	87.62
AUROC	95.55	93.15	98.26	**96.57**	96.70	94.65
AUPR	96.47	**46.54**	98.40	41.61	96.94	31.98

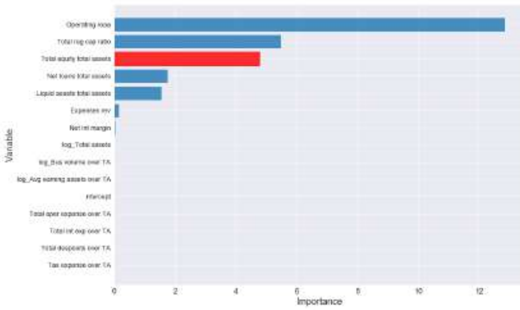
Source: Authors' calculations. All scores are defined in Section 2.5 and displayed in %. In red, the out-of-sample rate of failed banks identified as so.

2.5.1.2 Features' importance

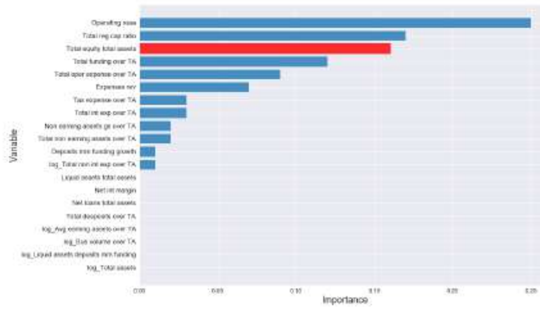
The next step in our study consists in determining which variables (features) impact the most the probability of bankruptcy. To do so, we compute the relative significance of the different features, resorting to the computation of the relative importance of features for the RF model (Hastie et al., 2009) and to that of the permutation feature importance for the ANN model (Breiman, 2001). Even if the importance of features is not calculated in the same way for our three models, such calculation allows in each case to rank features according to their importance and thus to gain insight on the main predictors of default. Figure 2.5.1 presents variables' relative importance for our three models.

Figure 2.5.1 – Variables' relative importance - US

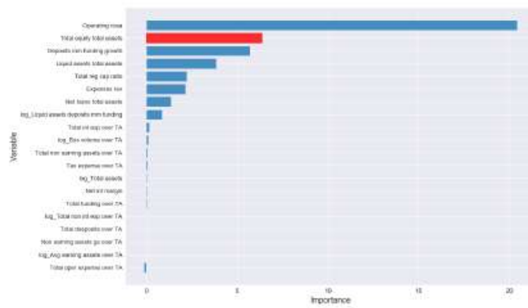
(a) Logistic regression



(b) Random Forest



(c) Artificial Neural Networks



Source: Authors' calculations. In red the importance of TE/TA ratio.

We notice that the three models exhibit more or less similar rankings. Operating Return On Average Assets (ROAA) always ranks first, which is not surprising and in line with the literature. Equity over total assets (TE/TA) always ranks among the top three predictors of banks' default. Total regulatory capital also ranks among the main predictors of default. In line with the simple theoretical model presented in Appendix 2.A, we notice that capital is a stronger predictor of bankruptcy than the proportion of liquid assets held.[10]

[10] The only situation where this is not the case is in the ANN model where total regulatory capital is less important than liquid assets over total assets. However, even in this case, equity over total assets is more important than the latter ratio.

2.5.1.3 Features' impact on default probability

Now that we have exhibited which variables are the main predictors of banks' failure, we have to wonder what is the impact of those variables on the probability of default. From a regulatory perspective it is indeed of the utmost importance to know on which variables focusing to design proper rules. We first begin by presenting the results drawn from the logit model. Results are presented in Table 2.5.2.

Table 2.5.2 Logistic regression - US

Variables	Odds Ratio	Coefficient p-values
Total equity total assets	-0.217***	0.000
Total reg cap ratio	-0.118***	0.000
Liquid assets total assets	0.079***	0.000
Expenses rev	-0.001***	0.000
Net int margin	0.748***	0.000
Net loans total assets	0.036***	0.000
Operating roaa	-0.626***	0.000
Tax expense over TA	-1.000***	0.000
Total desposits over TA	-0.481***	0.000
Total int exp over TA	2.5e+19***	0.000
Total oper expense over TA	-1.000***	0.000
log_Avg earning assets over TA	345.334***	0.000
log_Bus volume over TA	-0.984***	0.000
log_Total assets	-0.127***	0.000
intercept	1.539**	0.023
Nb. of observations	111502	
Nb. of banks (before SMOTE)	3138	
Nb. of defaults (before SMOTE)	331	

Source: Authors' calculations. Odds ratio are calculated as the exponential of estimated coefficients. To ease the reading, we have subtracted 1 from the OR. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

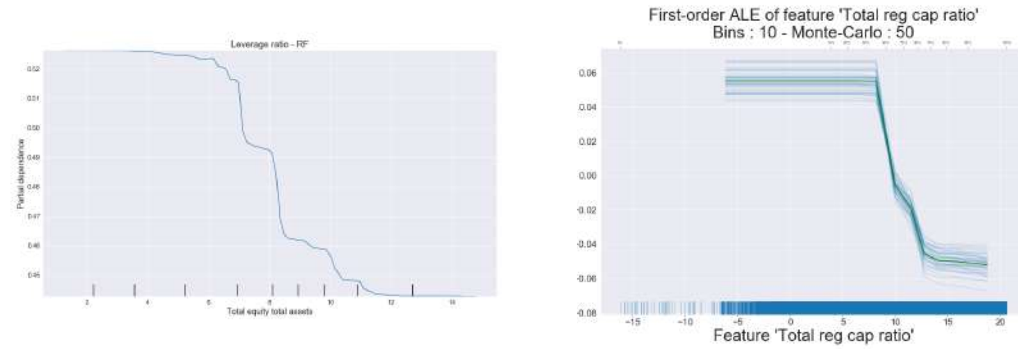
We notice that both total equity over total assets and total regulatory capital have a negative impact on the probability of default. More precisely, the total equity over total assets ratio has a stronger negative impact than total regulatory capital. This suggests that a simple constraint on the leverage ratio would perform better than a sophisticated capital ratio in preventing banks from defaulting. Surprisingly, the impact of liquid assets holding on the probability of default is positive, suggesting that the more banks hold liquid assets, the more they are likely to go bankrupt. This seems in contradiction with the simple theoretical model presented in Appendix 2.A. However, in this model, we assume that liquid assets yield the same return as that paid to depositors. This assumption was meant to simplify the interpretation of the results, but has the consequence to ensure a positive impact of liquid assets holding on the probability of default.[11] On the contrary, when liquid assets pay less than what banks have to pay to their depositors, it is likely that liquid assets holding will have a positive impact on the probability of default.

Tables 2.5.2 and 2.5.3 present results for, respectively, RF and ANN. In both cases, the results drawn from the logit model are confirmed: capital has a negative impact on the probability of default, while liquid assets holding has a positive effect.

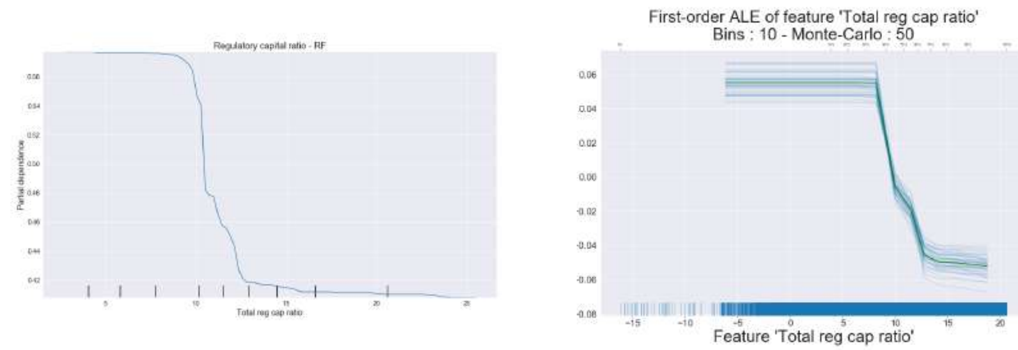
[11] This is however not a problem *per se* since our model has the only purpose to provide some insight on the absolute value of the impact of capital and liquid assets holding on the probability of default.

Figure 2.5.2 – PDP and ALE - RF classifier - US

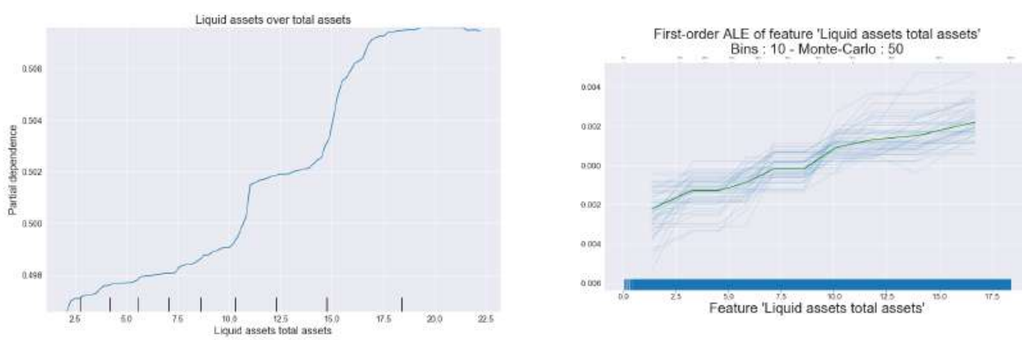
(a) Total equity over total assets



(b) Total regulatory capital



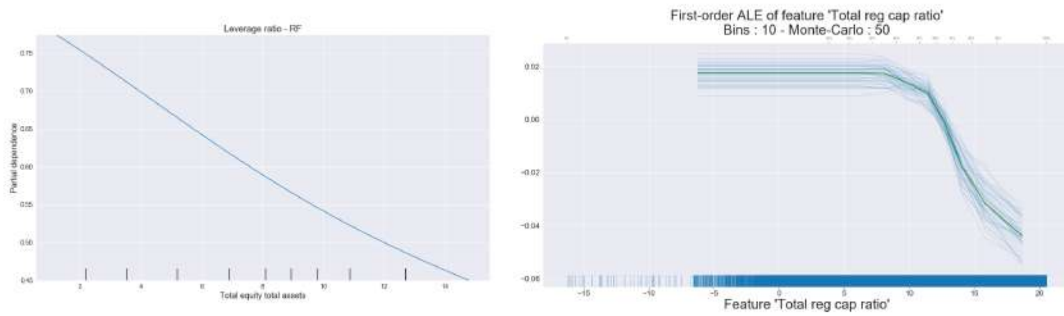
(c) Liquid assets over total assets



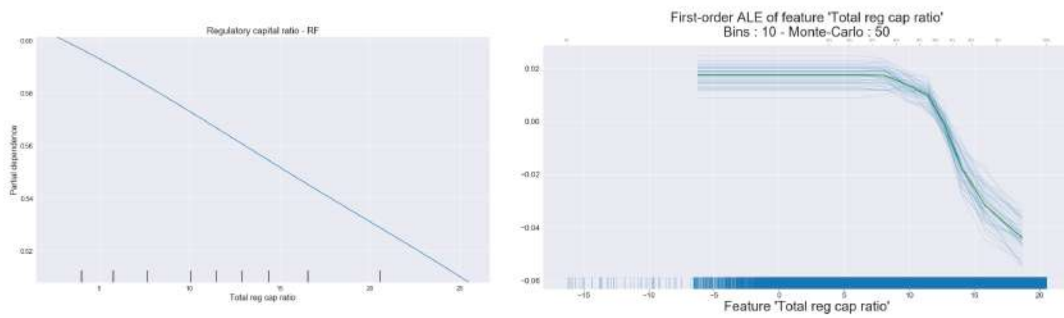
Source: Authors' calculations. PDPs on the left, ALEs on the right.

Figure 2.5.3 – PDP and ALE - ANN classifier - US

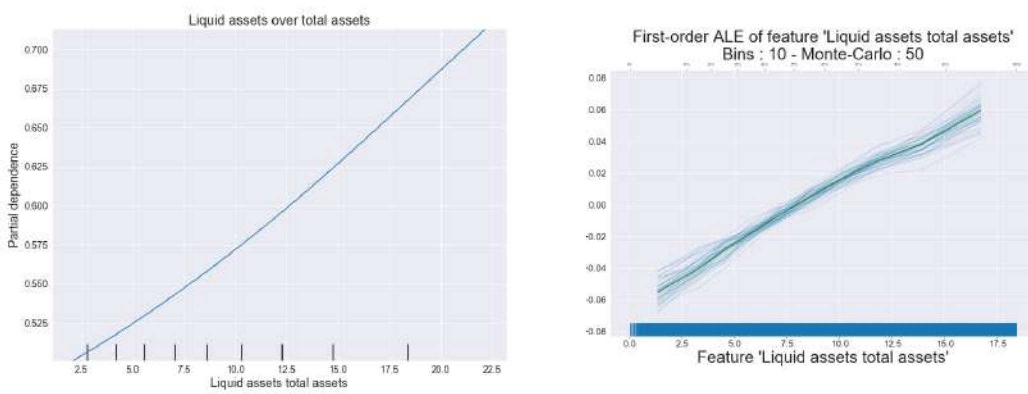
(a) Total equity over total assets



(b) Total regulatory capital



(c) Liquid assets over total assets



Source: Authors' calculations. PDPs on the left, ALEs on the right

In sum, capital has a negative impact on the probability of default, which confirms that it is indeed the main instrument through which banking regulation should intervene. In addition, it seems that the ratio equity over total assets is a stronger determinant of the probability of default than total regulatory capital.

As for liquid assets holding, it counter-intuitively appears that it has a positive impact on the probability of default. This result can be explained by the low return associated with liquid assets.

2.5.2 European banks

We now turn to the results concerning European banks. As already stated in the data section, the main difficulty when it comes to inquiring the question of bankruptcy prediction in the European context is that there does not exist a unique database identifying banks' defaults as is the case for the US. We therefore identify banks' defaults directly in the Fitch Connect database.

Table 2.5.3 presents the performance of our three models in predicting banks' default. Here again we resort to different measures of performance, with a particular focus on the true positive rate (TPR). Results are far less convincing than those for US banks. We indeed notice that our models perform less well than for US banks. The performance of the three models is however consistent, with none performing very differently from the others. The best model here may be RF since it performs better than the others out-of-sample, event if it predicts correctly only a little more than half of the defaults.

Table 2.5.3 Models' performance - Europe

Score	Logit		RF		ANN	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Score	67.24	62.87	86.07	74.68	69.74	50.06
TPR	70.92	53.01	96.69	51.81	83.97	65.06
TNR	63.56	63.0	75.46	74.98	55.52	54.93
AUROC	70.87	61.12	92.36	66.89	74.17	61.39
AUPR	62.99	1.9	89.93	2.26	65.85	1.94

Source: Authors' calculations. All scores are defined in Section 2.3 and displayed in %. In red, the out-of-sample rate of failed banks identified as so.

The difficulty to offer a satisfying prediction model of banks' default for European banks is certainly related to the lack of data concerning defaulting banks. As a consequence of the poor predictive power of our models, results on the importance and on the impact of features on the probability of default are hard to interpret. We nonetheless report those results in Appendix 2.D for the sake of completeness.

2.6 Robustness

2.6.1 Taking time dynamic into account

The results displayed in Section 2.5 are based on first-order lagged variables so that the default is predicted one year before its occurrence. However, it is possible that probability of default is more influenced by balance sheet variables in dynamic than in static terms. This view is supported by the variables' evolution displayed in Section 2.4.2: at least for US failed banks, we can observe a drop in some variables in the two to three years preceding default.

In this robustness check, we intend to account for this potential dynamic effect. To do so, we fit the model using first difference variables. Table 2.E.1 in Appendix

2.E.1 shows the performance scores of those estimations.

As can be seen, even if the results for Random Forest classification in the case of US banks are quite decent, most of the models using first difference variables display poor classification capacity. So, it is the balance sheet's state in the year before default that constitutes the main determinant of default.

2.6.2 Variables standardization

Standardization of independent variables is a usual procedure before implementing the models we use. It is supposed to decrease multicolinearity risks and ensure measurement units equivalence between features. However, we decided to keep our variables as they are for three reasons: (i) we control for multicolinearity issues during our modeling process, (ii) considering that we only have balance sheet variables, we do not believe the measurement units differences to be strong, and (iii) interpretation is much easier when keeping features in their original units.

Nevertheless, as a robustness check, we look into our models' performances when variables have been standardized. Table 2.E.2 in Appendix 2.E.2 gives the performance results for those models.

Results with standardized variables are similar to those obtained with untransformed variables. Particularly, the logistic regression performs slightly better with those variables. This finding was expected since standardization helps for multicolinearity treatment. Since performances are not deeply improved, we are comforted in the choice of displaying results with untransformed variables.

2.6.3 Alternative treatment of extreme rare events

As mentioned in Section 2.2, there are multiple ways to treat extreme rare events. We chose to proceed with the SMOTE procedure by comparing the estimation results with three other methods: the implementation of models on raw data, the use of class weighting, and the implementation of an anomaly detection methodology.[12]

Models with no treatment of extreme rare events are unsurprisingly outperformed by all the others.

Class weight methodology is based on King and Zeng (2001) and consists in weighting the data, resulting in a weighted log-likelihood. Even if the results are better than the precedent approach, we found that SMOTE procedure produces slightly higher performances.

As a robustness check, we also implemented a model used in anomaly detection, namely the autoencoder (Olshausen and Field, 1996). Autoencoder is built on a similar structure as Artificial Neural Networks. It consists in dimensionality reduction (encoder) and input reconstruction (decoder). It is used for anomaly detection as follows: the model is trained only on "normal" cases (non default in our case). Then, the testing data, that includes default events, is passed through the model. The prediction error is supposed to increase importantly when a failed banks' input occurs. We can therefore create a variable that scores 1 when the error exceeds a certain threshold (default) and 0 the rest of the time. In our case, the results for the autoencoder are not satisfying enough to privilege this

[12] Results are available upon request.

methodology to the other ones. Moreover, interpretability is far more complicated with this kind of deep learning methodology.

2.6.4 Reduced time dimension for the European sample

We noticed in Section 2.4.1 that there might be some issues in our data on European banks: the number of banks is very low until 2008 where it rises from 197 in 2006 to 1275 in 2008. In order to control for a potential data selection bias, we run our models on the sample going from 2008 to 2018. Table 2.E.3 in Appendix 2.E.3 displays the performance results for those estimations.

Compared to our results on the full period, the overall performance of models is slightly improved but no one shows better capacity to identified default. The global scores' enhancement is mainly due to better non default identification. We believe that this is due to the fact that reducing time dimension, we remove important information on default banks occurring between 2000 and 2007.

2.6.5 Reduced sample for logistic model

As mentioned earlier, logistic regression does not support multicolinearity issues. To tackle this issue, we drop most correlated variables with each-other in the regressions presented in Section 2.5. However, we observed high coefficients values associated with some variables, which is characteristic of multicolinearity. As a robustness check, we run logistic regressions for both US and Europe, removing variables associated with explosive coefficients.

Results for those models are displayed in Tables 2.E.4 and 2.E.5 in Appendix

2.E.4. We can see that models' performances and odds ratios' values are quite stable compared to those obtained with full features. Equity and capital ratios remain statistically significant and have negative influence on default probability. We can notice that the intercept takes high values in both models. This can be explained as follows: when all balance sheet variables are null, the probability of default equals 1.

2.7 Conclusion

In this chapter, we tackle one of the most essential aspects of banking regulation: do prudential rules prevent banks from going bankrupt? Indeed, Basel III accords are supposed to strengthen financial stability both through macro- and micro-prudential perspectives. We focus our study on the latter one by looking at the efficiency and impact of some prudential ratios on banks' probability of default. To this aim, we rely on large databases of 4707 US banks and 3529 European ones, with respectively 454 and 205 observations of default, over the 2000-2018 period. Using SMOTE procedure to balance our data, we apply three different approaches to classify failed banks from the others: logistic regressions, random forest classifications, and artificial neural networks.

Our results on the US sample show high classification performances and identify three main determinants of bankruptcy probability: profitability as measured by operating ROAA, total regulatory capital ratio, and total equity over total assets ratio. Our findings also underline strong negative impact of equity over total assets and regulatory capital ratios on default probability. Turning to liquid assets over total assets ratio, even though its predictive power of default probability is found to be weak, its impact is surprisingly assessed as positive. We justify this result by the fact that liquid assets are likely to have lower returns than deposits. Therefore, this finding must be seen in the particular context of the period covered by our study: low interest rates since the crisis at the end of the 2000s.

Overall, our investigation suggests regulatory requirements to focus more on capital than on liquidity. Moreover, since equity over total assets and regulatory capital ratios seem to have similar impact on banks default probability, we believe that the actual regulatory agreements would gain in terms of complexity costs if focusing on leverage ratio. Besides, as shown in Durand and Le Quang (2020), equity ratio has positive impact on profitability as measured by ROAA. Therefore, prudential framework based on fewer rules but higher leverage ratio could also create a healthy dynamic between leverage, profitability and distance to default.

Our findings on the European sample are far less convincing. Since the quality of the models is not as great as for US banks, the interpretation of the results is much more delicate. The poor quality of our estimations on the European sample can be explained in two manners: (i) their is too much uncertainty in our data since there is no official list of failed banks in Europe as there is in US, and (ii) the differences between US and European banking system structures are so important that it implies an unequivocal opposition in their banks default determinants. We do not believe that European banks failure cannot be explained by balance sheet variables at all, so the first reason is the most probable.

The health crisis of 2020 related to Covid 19 creates great uncertainty about its economic repercussions, and there may be an opportunity to see whether some lessons from the 2007 financial crisis have been learned. Specifically, the next few years are likely to test the strength and relevance of Basel III regulatory agreements. Therefore, the after crisis period will be the occasion to test our hypothesis on a more efficient regulation when based on strong leverage ratios.

Appendix

Appendix 2.A Why capital dominates liquid assets in predicting banks' failure: a theoretical insight

Let us assume a bank that invests in a portfolio of assets funding through both capital (in proportion $1-y$) and bonds (in proportion y). This portfolio is made both of a riskless asset (in proportion x) and of a risky asset (in proportion $1-x$). The balance sheet of the bank is thus as follows:

Asset	Liability
Risky Asset $(1-x)$	Bonds $(1-y)$
Riskless Asset (x)	Capital (y)

The risky asset pays a random return that it as follows: it pays $\pi > 1$ with probability p and 0 with probability $1-p$. We assume that bondholders are paid the riskless return 1. The bank is thus solvent whenever the following inequality holds:

$$x + (1-x)\pi p \geq (1-y) \iff p \geq p^* \equiv \frac{1-y-x}{(1-x)\pi}. \qquad (2.A.1)$$

p^* is therefore the threshold value of p such as when $p < p^*$ the bank ends up defaulting, and when $p \geq p^*$ the bank is solvent. More precisely, we have:

- when $y > 1 - x$, we have $p^* < 0$, the bank is always solvent,
- when $y \leq 1 - x$, the bank is solvent whenever $p \geq p^*$.

Let us differentiate p^* with respect to y:

$$\frac{\partial p^*}{\partial y} = -\frac{1}{(1-x)\pi} < 0. \tag{2.A.2}$$

Let us differentiate p^* with respect to x:

$$\frac{\partial p^*}{\partial x} = -\frac{y}{(1-x)^2\pi} < 0. \tag{2.A.3}$$

We notice that increasing capital always reduces more the probability of default than increasing liquid asset holding. We indeed have $\left|\frac{\partial p^*}{\partial y}\right| \geq \left|\frac{\partial p^*}{\partial x}\right| \iff y \leq 1 - x$. When $y > 1 - x$, we know that the bank is always solvent. In this very simplistic model, capital thus always dominates liquid assets as a regulatory tool to prevent bankruptcy.

Appendix 2.B Data sources and definitions

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Table 2.B.1 Data sources and definitions

Data	Definition	Source
Total equity total assets	Ratio of total equity to total assets. This ratio is close to the leverage ratio as defined under Basel agreements.	FitchConnect
Total reg cap ratio	Total regulatory capital ratio as defined under Basel agreements. It is fixed to 8% of the risk weighted assets, plus a conservation buffer (2%).	FitchConnect
Liquid assets total assets	Liquid assets detained by the bank over its total assets	FitchConnect
Net loans total assets	Ratio of net loans to total assets.	FitchConnect
Deposits mm funding growth	Growth rate of deposits to money market funding.	FitchConnect
Expenses rev	Expenses over revenues ratio.	FitchConnect
Net int margin	Returns on invested funds. It is measured by the difference between the interests received and those paid, divided by the average invested assets.	FitchConnect

Table 2.B.1 (continued)

Non earning assets gs over TA	All assets that do not generate income over total assets.	FitchConnect
Operating roaa	Ratio of net income to average total assets. It measures the profitability of assets, meaning how a firm uses the resources it owns to generate profit. It refers to the returns on the assets purchased using each unit of money invested.	FitchConnect
Tax expense over TA	Expense for current and deferred tax for the period over total assets.	FitchConnect
Total desposits over TA	Total deposits over total assets.	FitchConnect
Total funding over TA	Total Deposits, Money Market and Short-term Funding + Total Long Term Funding + Derivatives + Trading Liabilities, all over total assets.	FitchConnect
Total int exp over TA	Ratio of total interest expense / Total assets.	FitchConnect
Total non earning assets over TA	All assets that do not generate income, over total assets.	FitchConnect

Table 2.B.1 (continued)

Total oper expense over TA	Operating costs include administration costs such as staff costs, over total assets	FitchConnect
log Avg earning assets over TA	Logarithm of year assets that generate income, over total assets.	FitchConnect
log Total assets	Logarithm of total assets. It gives a proxy for banks' size.	FitchConnect
log Bus volume over TA	Logarithm Total Business Volume = Managed Securitized Assets Reported Off-Balance Sheet + Other off-balance sheet exposure to securitizations + Guarantees + Acceptances and documentary credits reported off-balance sheet + Committed Credit Lines + Other Contingent Liabilities + Total Assets. All over total assets.	FitchConnect
log Liquid assets deposits mm funding	Liquid assets as a deposit.	FitchConnect
log Total non int exp over TA	Non interest expenses over total assets.	FitchConnect

Appendix 2.C Methodology

2.C.1 Synthetic Minority Over-sampling Technique (SMOTE)

Introduced by Chawla et al. (2002), Synthetic Minority Over-sampling Technique is inspired by Ha and Bunke (1997) and is designed to address both the issues associated with imbalanced data and the limitations of over-sampling with replacement. This technique is built in such a way that it replicates the initial data distribution. It works as follows:

- We focus on the minority class: $E_{min} = \{i \in [\![1, N]\!] | y_i = 1\}$, N being the number of banks, y is the dependent variable that scores 1 at time $t-1$ when a bank fails in t and 0 otherwise
- For all individual j in E_{min}, we take the difference between its features x_j and their k nearest neighbors: $diff(x_j, knn(x_j))$
- $diff(x_j, knn(x_j))$ is then multiplied by a random factor rd selected between 0 and 1
- $diff(x_j, knn(x_j)) \times rd$ constitutes a new synthetic observation in the minority class

This process is then repeated until the desired weights of classes are reached. As mentioned in Section 2.3, this procedure is only applied on the training data set. Therefore, we can measure its efficiency by a simple comparison between out-of-sample scores of classification models with and without SMOTE applied to data.

2.C.2 Decision tress and Random Forest (RF)

Random Forest classification is a supervised statistical learning methodology that performs well out-of-sample (Hastie et al., 2009), and allows to capture non-linearities and interactions between variables.

The main idea behind the RF method is to average a more or less large number of decision trees. A tree is built by partitioning the space of explanatory variables into regions, and then by predicting an output value in each final region. The M final regions (or leaves) of the tree $\{R_m, m \in [\![1, M]\!]\}$, are obtained *via* recursive binary partitions. At each split of features space, we choose the variable for which the split gives the best fit of the output variable (or label). Once the tree is built, the estimated probability $\hat{p}_{1m}$ of default in region m is given by the proportion of default in the region:

$$\hat{p}_{1m} = \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i = 1)$$

where N_m is the cardinal of region m, m is the region with $m \in [\![1, M]\!]$, $I(y_i = 1)$ is the function that scores 1 if y_i equals 1 and 0 otherwise. Therefore, this method is a non-parametric estimation of the unknown function f. This function defines the true model: $P(y = \{0, 1\}|X = x) = f(x) + \epsilon$, where ϵ designates the error term.

The best splitting point is computed for all variables and the variable for which the splitting point gives the best minimization of the criterion is chosen. We use the Gini index impurity measure (criterion to minimize) given by (Hastie et al., 2009):

$$\sum_{k \neq k'} \hat{p}_{mk}\hat{p}_{mk'} = \sum_{k=0}^{1} \hat{p}_{mk}(1 - \hat{p}_{mk})$$

The second step in building a decision tree is to determine the maximum depth of a tree and the minimum number of observations in every leaves. Indeed, shallow trees are likely to have poor prediction performance, and too deep trees might lead to overfitting issues and consequently bad out-of-sample forecasting. Following the same logic, a large number of observations per final region will predict poorly, while too little observations per leave are also subject to overfitting problems.

Thus, the determination of those two parameters (depth and observations per leave) is crucial and can be done in various ways. In the context of a single tree, Hastie et al. (2009) propose to rely on a cost complexity criterion that should be minimized. This procedure works on the fact that an increase in complexity (measured by the depth of the tree) that leads to overfitting the data and decreases the sum of squares is counterbalanced by an increase in a cost term that depends on the tree's depth. In the context of RF, this approach is quite demanding in terms of calculation: the criterion must be minimized for each tree. Another technique consists in making varying those two parameters in multiple RF classification estimations simultaneously and retain those that maximize the out-of-sample prediction performance.

The last parameter to establish is the number of trees in the forest. There are some debates on the optimal value for this parameter (and the very existence of an optimum). Hastie et al. (2009) suggest that the error of the model generally decreases and converges as the number of trees grows. From this perspective, the right number of trees corresponds to the moment where the error does not decrease below a certain threshold.

2.C.3 Artificial Neural Networks (ANN)

Artificial Neural Networks, introduced by McCulloch and Pitts (1943), also constitute a supervised statistical learning methodology that has gained attention in recent decades, in an increasing number of areas (Hastie et al., 2009). The general principle of ANN is to stem features T_k by linear combinations of the inputs Z_m and then predict output values $f_k(X)$ from a non-linear function $g_k(.)$ applied to those features. In a binary classification model, it gives:

$$Z_m = \sigma(\alpha_{0h} + \alpha_h^T X),\ h \in [\![1, H]\!]$$

$$T_k = \beta_{0k} + \beta_k^T Z,\ k \in \{0, 1\}$$

$$f_k(X) = g_k(T),\ k \in \{0, 1\}$$

where $\sigma(.)$ is the simoid function given by $\sigma(v) = \frac{1}{1+e^{-v}}$, H is the number of hidden units in the hidden layer, and $g_k(.)$ is the softmax function given by $g_k(T) = \frac{e^{T_k}}{\sum_{l \in \{0,1\}} e^{T_l}}$. We note the full set of parameters, or weights, θ:

$$\{\alpha_{0,h}, \alpha_h; h \in [\![1, H]\!]\}$$

$$\{\beta_{0,k}, \beta_k; k \in \{0, 1\}\}$$

The error function to minimize is given by the cross-entropy measure:

$$R(\theta) = -\sum_{i=1}^{N} \sum_{k \in \{0,1\}} y_{ik} \log(f_k(x_i))$$

As specified by Hastie et al. (2009), the research for the global minimizer of $R(\theta)$ is likely to lead to overfitting issues. This is managed by either early stopping procedure or penalization term. The parameters of the model are estimated *via* gradient descent, and the gradient is computed using the back-propagation algorithm. This algorithm works as follows:

- Initial values for the weights are randomly chosen, generally close to zero
- The weights begin fixed, predicted value $\hat{f}_k(X)$ is computed
- This prediction allows to assess errors in the output δ_k and hidden layer s_m, that are used in the gradient computation
- The gradient is finally used to adjust the weights

ANN training must be performed with some precautions regarding some aspects. Considerations on the initial values of weights must be done for two reasons: (i) too small values will lead the network to collapse into a linear model,[13] and (ii) multiple values for the initial weights should be tested since $R(\theta)$ is non-convex and that the final solution can vary in function of those. As mentioned above, because of the important number of parameters, the search for a global minimum of R might lead to overfitting. To avoid this, a regularization (or penalization) term can be added to the error function that we seek to minimize. This hyperparameter

[13] Usually, we choose values close to zero. The network is then an approximately linear model and becomes more non-linear as the weights increase.

can be optimized through multiple regression. Finally, it is worth mentioning that the final prediction of a network can depend on the fact that inputs have been scaled or not. This can be controlled by comparing results on both models: with and without scaled features.

2.C.4 Partial Dependence Plots (PDP)

Partial Dependence Plots (Friedman, 2000; Hastie et al., 2009) belong to quantitative input influence techniques to visualize features' impact on labels in opaque models. A PDP provides a summary of the output dependence on the joint values of the inputs (Friedman, 2000; Hastie et al., 2009). Considering a subset of $l < p$ inputs $X_{S,S \subset \{1,2,...,p\}}$ of $X^T = (X_1, ..., X_p)$, such that $f(X) = f(X_S, X_{S^C})$,[14] the partial dependence of f to X_S is given by:

$$f_S(X_S) = E_{X_{S^C}} f(X_S, X_{S^C}).$$

Note that this equation defines a measure of X_S effect on $f(X)$ after accounting for X_{S^c} effect. To calculate this impact in practice, we proceed as follows. We first assess Individual Conditional Effect (ICE), meaning the partial dependence of $f(X)$ on X_S when considering values of X_{S^c} for a given individual i:

$$ICE_i = \{\hat{f}(x_S^k, X_{i,S^C}), x_S^k \in [X_S^{min}, X_S^{max}]\}, \tag{2.C.1}$$

[14] S^C being the complementary of S: $S \cup S^C = \{1, 2, ..., p\}$.

where ICE_i is the ICE for the i-th individual, X_{i,S^C} refers to values of X_{S^C} of this individual, and x_S^k are the values of X_S that vary from its minimum to its maximum with a step k. This provides a set of points representing a plot of partial dependence of the explained label on the variables included in S for the i-th individual. In a second step, we average those plots for all the individuals, and we obtain the PDP.

2.C.5 Accumulated Local Effects (ALE)

One of the most important issues in PDPs is that they assume independence between the predictor for which the partial dependence is computed and the other one. Besides, making x_S^k vary across all the distribution of X_S creates a risk to overfit regions with almost no data. In order to overcome this issue, we rely on Accumulated Local Effect (ALE) (Datta et al., 2016) .

ALE also proposes to calculate the marginal effect of X_S. The main differences with PDP can be summarized as follows: ALE is unbiased even when features are correlated, it marginalizes over probable combinations of features, and it is faster to compute. Technically, ALE bases its calculation on existing data intervals for explanatory variables. Moreover, ALE averages the changes of predictions, not the predictions themselves. Another significant difference with PDP is that ALE accumulates the local gradients over the range of features S, giving their effect on the predicted variable. Finally, ALE method is centred so that the average effect is zero.

In practice, ALE for one given feature is computed, dividing it into many intervals, and computing the differences in the predictions.[15] First, the uncentred effect is calculated:

$$\hat{\tilde{f}}_j(x) = \sum_{k=1}^{k_j(x)} \frac{1}{n_j(k)} \sum_{i:x_j^{(i)} \in N_j(k)} [f(z_{k,j}, x_{\setminus j}^{(i)}) - f(z_{k-1,j}, x_{\setminus j}^{(i)})],$$

where $\hat{\tilde{f}}_j(x)$ is the uncentred effect of the variable j. $f(z_{k,j}, x_{\setminus j}^{(i)})$ gives the prediction given by the model, and considers the i-th individual for features values excepted x_j that takes the value $z_{k,j}$. The z are the values taken by the variable X_j that has been distributed on a grid defined by a given step. The internal sum adds up the impacts of all individuals within an interval $(i : x_j^{(i)} \in N_j(k))$ that appears as a neighbourhood. This sum is weighted by the number of individuals $n_j(k)$ present in the k-th neighbourhood. Finally, we sum the average effect over all intervals. Second, we center in order to obtain a null main effect:

$$\hat{f}_j(x) = \hat{\tilde{f}}_j(x) - \frac{1}{n} \sum_{i=1}^{n} \hat{\tilde{f}}_j(x^{(i)})$$

$\hat{f}_j(x)$ is interpreted as the main impact of the explanatory variable compared to the average prediction of the data.

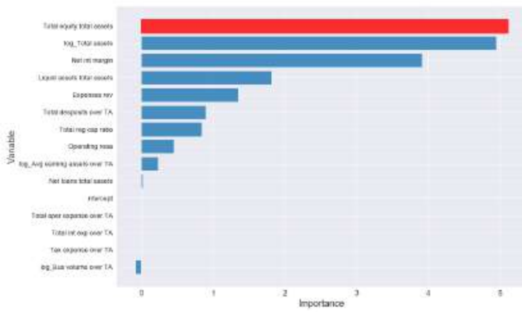
[15] This approximates the local gradients and allows us to compute ALE using RF classification, as well as ANN.

Appendix 2.D Results for Europeans banks

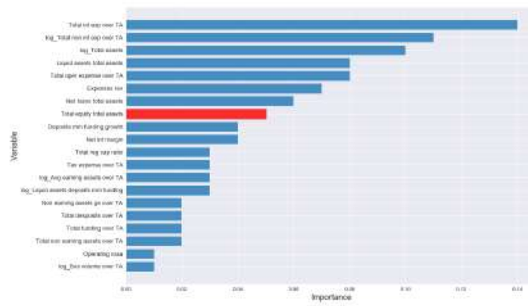
2.D.1 Features' importance

Figure 2.D.1 – Variables relative importance - Europe

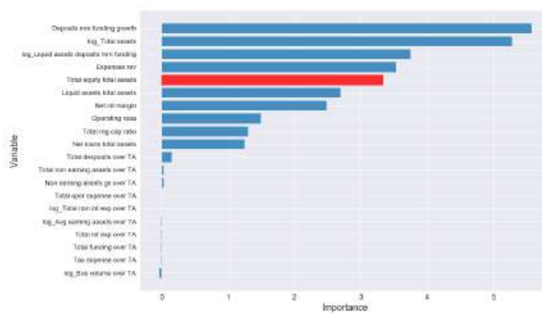
(a) Logistic regression



(b) Random Forest



(c) Artificial Neural Networks



Source: Authors' calculations.

2.D.2 Features' impact on default probability

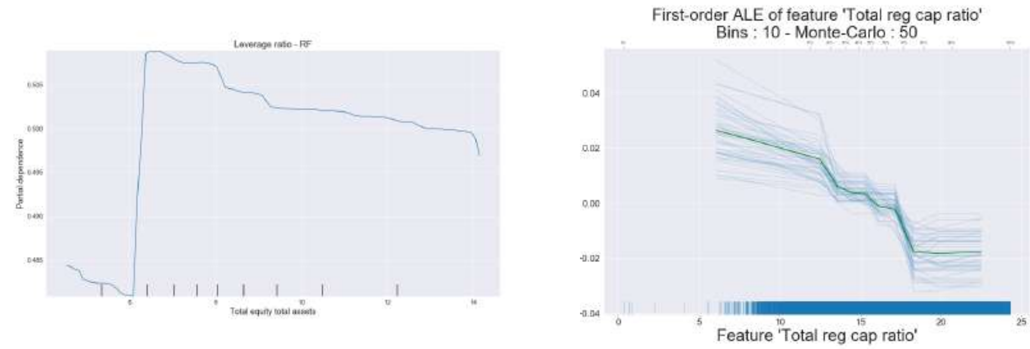
Table 2.D.1 Logistic regression - US

Variables	Odds Ratio	Coefficient p-values
Total equity total assets	-0.157***	0.000
Total reg cap ratio	-0.051***	0.000
Liquid assets total assets	0.016***	0.000
Expenses rev	0.003***	0.000
Net int margin	0.232***	0.000
Net loans total assets	-0.011***	0.000
Operating roaa	-0.192***	0.000
Tax expense over TA	2.3e+57***	0.000
Total desposits over TA	-0.464***	0.000
Total int exp over TA	5.370	0.160
Total oper expense over TA	17.781***	0.001
log_Avg earning assets over TA	2114.767***	0.000
log_Bus volume over TA	-0.889***	0.000
log_Total assets	-0.375***	0.000
intercept	4029.465***	0.000
Nb. of observations	111502	
Nb. of banks (before SMOTE)	3138	
Nb. of defaults (before SMOTE)	331	

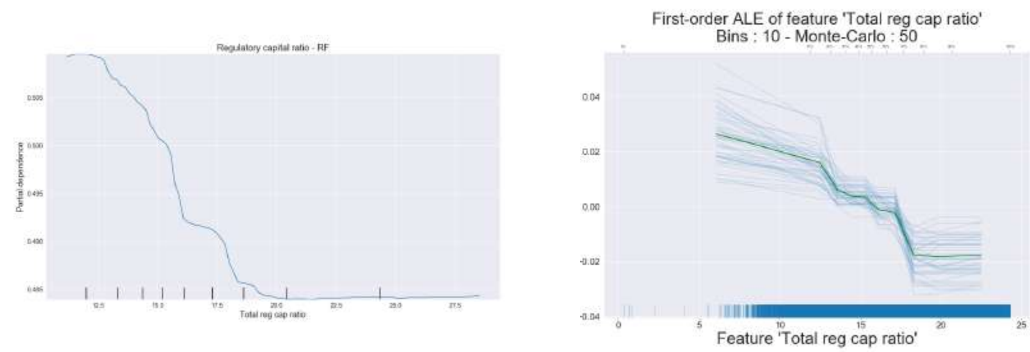
Source: Authors' calculations. Odds ratio are calculated as the exponential of estimated coefficients. To ease the reading, we have subtracted 1 from the OR. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

Figure 2.D.2 – PDP and ALE - RF classifier - Europe

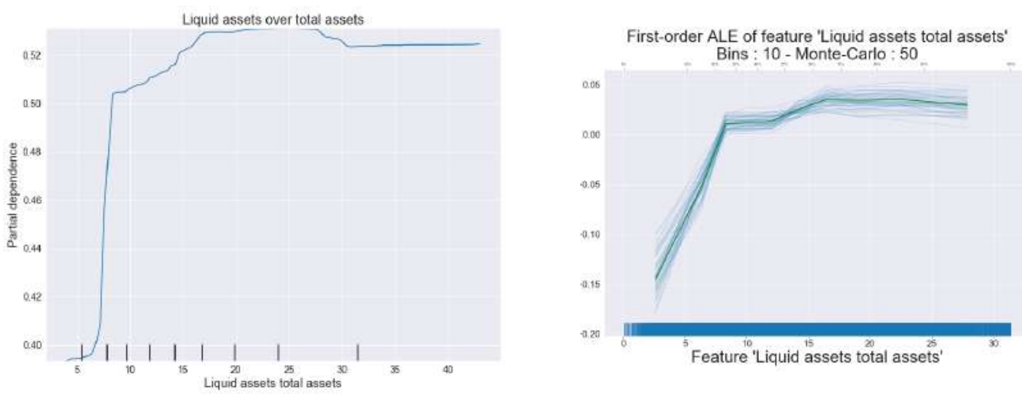
(a) Total equity over total assets



(b) Total regulatory capital



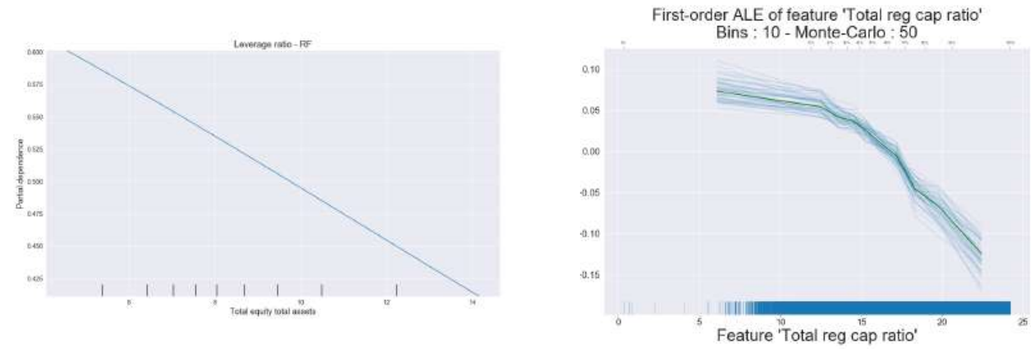
(c) Liquid assets over total assets



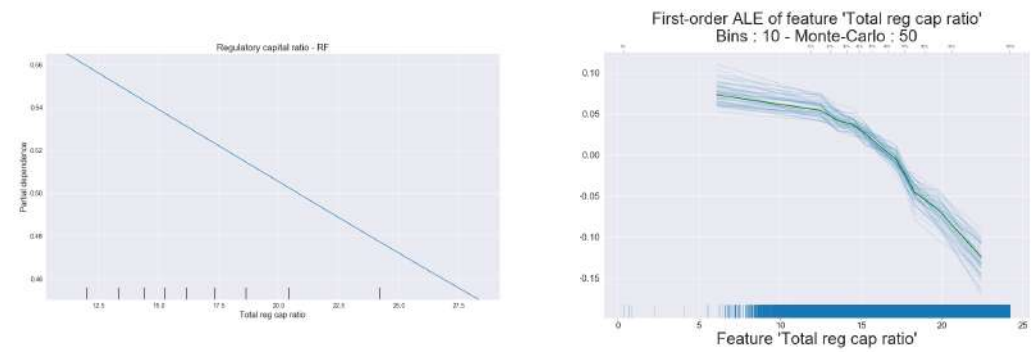
Source: Authors' calculations. PDPs on the left, ALEs on the right.

Figure 2.D.3 – PDP and ALE - ANN classifier - Europe

(a) Total equity over total assets



(b) Total regulatory capital



(c) Liquid assets over total assets

Source: Authors' calculations. PDPs on the left, ALEs on the right

Appendix 2.E Robustness outputs

2.E.1 Models with first difference

Table 2.E.1 Dynamic models' performance - US versus Europe

Scores	Logit		RF		ANN	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
			US			
Score	72.43	84.16	91.38	95.50	64.03	49.94
TPR	60.57	61.34	86.76	83.19	77.56	78.15
TNR	84.3	84.29	96.01	95.57	50.19	49.83
AUROC	72.18	69.74	97.13	96.16	76.58	77.32
AUPR	80.28	24.82	97.33	29.34	83.31	10.93
			Europe			
Score	62.02	67.23	95.59	89.38	53.55	48.38
TPR	66.25	55.32	99.66	17.02	58.62	46.81
TNR	54.83	55.11	91.54	90.02	48.5	48.4
AUROC	63.73	54.95	99.44	61.63	52.67	44.43
AUPR	62.79	0.92	99.38	1.2	49.71	0.71

Source: Authors' calculations. All scores are defined in Section 2.3 and displayed in %. In red, the out-of-sample rate of failed banks identified as so.

2.E.2 Standardized variables

Table 2.E.2 Models with standardized variables performance - US versus Europe

Scores	Logit		RF		ANN	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
			US			
Score	90.41	98.90	93.40	92.51	96.97	78.11
TPR	86.91	89.43	90.05	86.99	97.44	83.74
TNR	93.91	93.86	96.77	96.68	96.51	96.29
AUROC	96.49	80.44	98.25	92.46	99.49	70.80
AUPR	96.89	24.43	98.40	11.53	99.39	32.87
			Europe			
Score	68.75	63.01	82.06	71.77	84.36	48.38
TPR	73.74	55.42	91.53	53.01	90.12	40.96
TNR	63.76	63.11	72.6	72.02	78.61	78.15
AUROC	72.82	63.09	89.49	41.56	91.45	56.10
AUPR	65.93	2.16	87.21	2.26	89.27	11.11

Source: Authors' calculations. All scores are defined in Section 2.3 and displayed in %. In red, the out-of-sample rate of failed banks identified as so.

2.E.3 Reduced time dimension for Europe

Table 2.E.3 Models' performance on the 2008-2018 period - Europe

Score	Logit		RF		ANN	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Score	67.28	65.57	86.64	78.88	71.25	59.40
TPR	68.72	54.76	94.47	45.24	83.71	61.9
TNR	65.89	65.66	78.83	79.15	58.79	59.39
AUROC	72.30	65.47	94.59	70.60	77.11	65.32
AUPR	65.08	1.15	93.04	1.43	70.64	1.27

Source: Authors' calculations. All scores are defined in Section 2.3 and displayed in %. In red, the out-of-sample rate of failed banks identified as so.

2.E.4 Reduced number of independent variables for the logistic regression

Table 2.E.4 Logistic regression in reduced number of features - US versus Europe

Scores	Logit	
	In-sample	Out-of-sample
US		
Score	90.67	94.95
TPR	86.36	85.37
TNR	95.0	95.0
AUROC	95.55	93.14
AUPR	96.47	46.53
Europe		
Score	66.73	62.44
TPR	70.44	53.01
TNR	63.03	62.56
AUROC	70.22	62.27
AUPR	60.85	1.87

Source: Authors' calculations. All scores are defined in Section 2.3 and displayed in %. In red, the out-of-sample rate of failed banks identified as so.

Table 2.E.5 Logistic regression - US versus Europe

	US		Europe	
Variables	Odds Ratio	Coef. p-values	Odds Ratio	Coef. p-values
Total equity total assets	-0.239***	0.000	-0.138***	0.000
Total reg cap ratio	-0.111***	0.000	-0.053***	0.000
Liquid assets total assets	0.064***	0.000	0.010***	0.000
Expenses rev	-0.001***	0.000	0.000	0.421
Net int margin	0.259***	0.000	0.202***	0.000
Net loans total assets	0.047***	0.000	-0.012***	0.000
Operating roaa	-0.543***	0.000	-0.078***	0.000
Total desposits over TA	-0.901***	0.000	-0.417***	0.001
Total int exp over TA	-	-	1.286	0.494
log_Bus volume over TA	-0.997***	0.000	-0.798***	0.000
log_Total assets	-0.180***	0.000	-0.376***	0.000
intercept	9182.38***	0.000	650047.95***	0.000

Source: Authors' calculations. Odds ratio are calculated as the exponential of estimated coefficients. To ease the reading, we have subtracted 1 from the OR. Significance at 1%, 5%, 10% identified by ***, **, and *, respectively.

Chapitre 3

Banks to basics! Why banking regulation should focus on equity[†]

[†]Ce chapitre est publié en tant que Document de travail : Pierre Durand et Gaëtan Le Quang (2020), "Banks to basics! Why banking regulation should focus on equity", Working Paper EconomiX 2020-2. Nous sommes particulièrement reconnaissant envers Valérie Mignon et Laurence Scialom pour leurs conseils et remarques. Une première version avait été publiée en tant que Document de travail EconomiX (Pierre Durand (2019), "Determinants of banks' profitability: Do Basel III liquidity and capital ratios matter?", Working Paper EconomiX 2019-24) et je remercie grandement Gaëtan Le Quang pour notre collaboration qui a donné une dimension beaucoup plus "engagée" à ce travail. Je remercie également Benjamin Egron pour ses conseils et commentaires.

3.1 Introduction

Banking regulation proved inadequate to prevent the banking system from collapsing at the end of the 2000s. Massive public bailouts thus occurred and banking regulators began to work on a new framework meant to make it possible to contain the risk inherent to banking activities. This risk is now known as being systemic and as striking both sides of the balance sheet. Macroprudential tools – such as regulatory countercyclical buffers – and liquidity requirements – such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) – have therefore been put in place to tackle the threats posed by the specific nature of banking risk. In addition, bail-in instruments have been designed to prevent costly bailouts from occurring whenever a bank deemed too big to fail goes bankrupt.

Banking regulation has thus evolved after the 2007-2008 financial collapse. The macroprudential shift that began right after the crisis seems to lead banking regulation in the right direction. However, knowing that the previous financial crisis was, among other reasons, due to the very complexity of the financial system,[1] it is quite surprising to notice that the regulatory framework newly designed is very complex. The first pillar of Basel III indeed states that banks have to comply with two liquidity ratios, one leverage ratio and a risk-based capital ratio. Two bail-in standards – the Total Loss Absorbing Capacity (TLAC) that concerns systemic banks and the Minimum Requirement for own funds and Eligible Liabilities (MREL) that concerns every bank located in the European Union – have

[1]This complexity was the direct consequence of the great promotion of financial innovation during the 2000s.

additionally been put in place to protect taxpayers from bailouts. This complexity paves the way for criticism coming from the banking industry, arguing that such a multiplication of rules can only hamper banks' activity.[2]

The objective of this chapter is to suggest that banking regulation would be better off focusing more on equity instead of relying on complex and less transparent rules. We argue that implementing a strong constraint in equity would have the advantage of being both more transparent and more efficient than the current regulatory framework. Such a constraint is strongly opposed by the banking industry that argues that it would presumably cost a lot to society as a whole because of the restrictions in bank lending that would follow. The argument here is that increasing equity requirements would necessarily augment funding costs and thus hamper banks' lending activity. As Admati et al. (2013) show, this is a fallacious argument. Those authors indeed point out that a sharp increase in equity requirements would more likely have the opposite effect. Their idea is that since increasing equity requirements decrease the risk associated with banks' activities, they can issue bonds at a lower cost and, therefore, their total funding cost could decrease instead of rising as is often argued. Gambacorta and Shin (2018) provide empirical evidence that an increase of 1 percentage point in the ratio of equity over total asset yields a decrease of 4 basis points in the cost of debt for a sample of banks located in the G10 countries. In other words, increasing equity requirements could decrease banks' funding cost and thus eventually improve their performance. There is therefore no economic reason to oppose to a strong increase in equity

[2]In January 2020, the French Parliament voted against the full implementation of Basel III arguing mainly that it would impede banks' activities too much.

requirements.

Our chapter provides empirical evidence to support this idea. To do so, we use random forest (RF) regressions on a large dataset of banks' balance sheet variables over the period 2000-2018 in 21 countries to assess the predictive power of a large number of variables on several measures of banks' performance. The key contribution of our chapter is to show that the ratio equity over total assets ($\frac{\mathrm{E}}{\mathrm{TA}}$) has a strong quasi-linear positive impact on banks' performance as measured by the return on average assets (ROAA). Far from impeding banks' profitability, high equity requirements could thus foster it. On the contrary, we show that the ratio $\frac{\mathrm{E}}{\mathrm{TA}}$ has a non-linear impact on the return on average equity (ROAE). In particular, when the ratio $\frac{\mathrm{E}}{\mathrm{TA}}$ is below approximately 10%, the ROAE is negatively impacted by an increase in this ratio. The shareholder value is thus most of the time negatively affected by an increase in $\frac{\mathrm{E}}{\mathrm{TA}}$, which is probably the main reason why the banking industry opposes higher constraints in equity. The main cost associated with an increase in equity requirements is, therefore, supported by shareholders (since the ROAE decreases when $\frac{\mathrm{E}}{\mathrm{TA}}$ increases) and not by other stakeholders (since the ROAA increases when $\frac{\mathrm{E}}{\mathrm{TA}}$ increases). This is the main insight of our chapter.[3]

The methodological novelty introduced by the chapter is the use of RF regressions to assess the impact of various variables on banks' performance. The rationale behind this approach is that it allows considering the impact of a large number

[3]This is totally in line with the conclusion of Admati et al. (2013): "Most importantly, the cost to shareholders is entirely a private cost based on being able to benefit at the expense of creditors or taxpayers when there is less equity in the mix. Thus, it does not establish any social cost to increased equity requirements." (p.36).

of determinants and to range them according to their predictive power. Doing so we show that the ratio $\frac{E}{TA}$ is among the best predictors of banks' performance. Allowing for such a comprehensive dataset is one of the reasons why we chose to resort to RF regressions instead of more standard methods. Three other reasons also justify this choice. First, RF regressions do not impose to choose a specific functional form. Second, RF regressions incorporate both a procedure for estimating the determinants (or features) and their impact on the explained variable (or label). Third, RF regressions perform well out-of-sample (Hastie et al., 2009). In order to ensure the stability and soundness of our results, we provide several robustness checks: (i) we consider different measures of banks' performance, (ii) all results are compared to those of a Lasso model, (iii) all simple RF regressions' outcomes are compared with the mean of numerous (50 to 100) RF regressions run on random sample selection, and (iv) estimations are run on two samples.

This chapter lies in the literature on the determinants of banks' performance. Part of this literature deals with the impact of capital on profitability. No consensus is however to be found. Some papers conclude on the existence of a positive relationship between capital and profitability (Berger, 1995; Iannotta et al., 2007; Lee and Hsieh, 2013*a*). This positive relationship is explained by lower default probability and a decrease in funding costs. Other papers provide evidence of a negative relationship, justified by the existence of a "low-risk anomaly" and difficulties for high-capitalized bank to diversify their activity (Goddard et al., 2013; Baker and Wurgler, 2015). Fewer papers are dedicated to studying the impact of liquidity on profitability. On the one hand, holding liquid assets decreases the maturity mismatch and thus the liquidity risk. Banks that hold a large proportion of their asset portfolio in liquid assets thus benefit from low funding costs since they are less likely to go bankrupt, which has a positive impact on their performance (Berger and Bouwman, 2009; Bordeleau and Graham, 2010). On the other hand, liquid assets generate low returns and therefore low revenues. In this perspective, banks that hold a large amount of liquid assets are likely to perform less than banks investing in riskier assets (Goddard et al., 2013; Molyneux and Thornton, 1992). Apart from the impact of capital and of liquid assets holding on profitability, the literature focuses on other determinants of profitability such as market concentration (Bourke, 1989; Dietrich and Wanzenried, 2014; Molyneux and Thornton, 1992), cash and bank deposits (Bourke, 1989; Molyneux and Thornton, 1992), credit risks and loan loss provisions (Dietrich and Wanzenried, 2014; García-Herrero et al., 2009), tax variables (Albertazzi and Gambacorta, 2009; Chia and Whalley, 1999) and non-performing loans (García-Herrero et al., 2009). The impact of macroeconomic variables on profitability has also been assessed by many papers, for instance the impact of GDP growth rates (Bordeleau and Graham, 2010; Dietrich and Wanzenried, 2014), that of inflation (Bordeleau and Graham, 2010; Bourke, 1989; Dietrich and Wanzenried, 2014) and that of monetary policy (Borio et al., 2017).

To our knowledge, our chapter is the first to resort to RF regressions to investigate the determinants of banks' performance. Doing so and as stressed above, we show that the ratio equity over total assets is one of the main predictors of the performance when measured as the ROAA, and has furthermore a linear and positive impact on it. This is a major debunking of the idea according to which designing strong equity requirements would necessarily impede banks' activity and thus have an adverse impact on society as a whole. As a consequence, this chapter provides support to the definition of a strong constraint in equity instead of the multiplication of rules that could each have potentially harmful unexpected consequences.

The remainder of this chapter is structured as follows. Section 3.2 provides a brief overview of the regulatory framework that has been put in place after the crisis and presents the tested hypotheses. The methodology is discussed in Section 3.3. Data are presented in Section 3.4 alongside with some descriptive statistics. Section 3.5 reports the results, and robustness checks are provided in Section 3.6. Section 3.7 concludes.

3.2 Regulatory framework and tested hypothesis

This section provides an overview of the key novelties introduced by banking regulators after the crisis. Then, we formulate the hypothesis that will be tested using RF regressions.

3.2.1 A brief overview of the regulatory framework

As already mentioned, banking regulation has been renewed after the crisis. However, in spite of the diagnosis that was formulated right after the crisis (i.e., the necessity to contain systemic risk through proper macroprudential policies), the regulatory framework that is currently implemented is somewhat disappointing (Baker, 2013). Capital requirements have indeed barely been strengthened, liquidity regulation is ill-designed, and bail-in instruments could have unexpected harmful consequences. We detail all these points here.

Capital requirements have been modified after the crisis. In particular, the definition of regulatory capital has been tightened and many hybrids that were used to be integrated in regulatory capital are now ruled out. Banks now have to hold at least 7% of their risk-weighted assets in core capital compared to 2% under Basel II. Core capital requirements have thus been strengthened. However, as Admati et al. (2013) state it, a lot more can be done in this direction. In fact, the implementation of bail-in standards in addition to the capital constraints defined in the first pillar of Basel III can be interpreted as a palliative for low core capital requirements (Persaud, 2014).

Both the TLAC and the MREL define constraints in what is called eligible liabilities. Those are financial instruments that are associated with a high loss-absorbing capacity in the event where the issuing bank goes bankrupt. Contingent convertible bonds (coco bonds) are such eligible liabilities. They are bonds that behave like regular bonds in normal times but are converted into equity whenever a pre-defined event occurs. The main purpose of such bonds is to make it possible for banks to fund themselves by issuing bonds that are cheaper than equity and to make them benefit nonetheless from a loss-absorbing capacity similar to that of equity. Coco bonds are however not a panacea. They indeed could serve as a channel through which systemic risk could materialize. For instance, Corcuera et al. (2014) show that because of the conversion risk, coco bonds exhibit a death-spiral effect. To hedge the conversion risk, coco bonds' holders may indeed short sell shares. Doing so they may find themselves in a position of selling shares whose price is decreasing and, therefore, they may contribute actively to the materialization of the conversion risk. By hedging the conversion risk, investors thus make it more likely. Hence the spiral effect. Bologna et al. (2018) provide empirical evidence that shows how contagion can spread in the coco bonds market. Using two stress episodes that affected the European coco bonds market in 2016, the authors exhibit a significant coco bonds-specific contagion that can be the consequence of the reassessment by investors of coco bonds' riskiness. Coco bonds are thus complex financial instruments that could eventually act as a channel through which systemic risk propagates. Expectations of conversions could indeed nourish self-fulfilling panic sales of coco bonds and thus precipitate a market-wide panic that could spread to the whole financial system (Le Quang, 2019). It is therefore of the utmost importance to keep in mind that one of the reasons why the global financial crisis was so severe was because the systemic risk associated with securitized products had been largely overlooked. The current will to ensure financial stability through complex financial instruments, such as coco bonds, thus appears as a dangerous oversight of history. This is one of the reasons why contingent capital must not be used as a palliative for equity (Admati et al., 2013).

Liquidity regulation has been implemented through two different rules: the LCR and the NSFR. The LCR states that banks need to hold enough high quality liquid assets (HQLA) to withstand a liquidity crisis lasting 30 days. In other words, banks need to hold enough liquid assets to cope with their short-term liquidity needs. The NSFR states that banks' illiquid assets need to be funded through stable funding instruments. The first question that arises when looking at current liquidity regulation is why two ratios instead of one. Having a closer look at them, we notice that the two ratios are in fact redundant. Let us demonstrate it through an example.[4] Consider a bank whose asset portfolio is made both of liquid and illiquid assets that are funded through runnable and not-runnable liabilities. The balance sheet of the bank is thus as follows:

Asset	Liability
Liquid assets (LA)	Runnable liabilities (RL)
Illiquid assets (IA)	Not-runnable liabilities (NRL)

.

The LCR is met whenever $LA > RL \iff LA - RL > 0$. The NSFR is met whenever $NRL > IA \iff NRL - IA > 0$. The balance sheet identity states that $LA + IA = NRL + RL$. In other words, we have $LA - RL = NRL - IA$. As a consequence, whenever the LCR is binding, the NSFR is binding too and *vice versa*. The two ratios are thus likely to be redundant since when one is binding, the other is necessarily binding too. Instead of two ratios, liquidity regulation would thus be better off defining only one ratio. This would be a first step towards reducing the complexity of the regulatory framework. Which ratio should then

[4] The reasoning comes from Bolton et al. (2019).

be ruled out and which should remain? The difference between the two ratios is the side of the balance sheet on which they focus: the LCR focuses on the asset side, while the NSFR focuses on the liability side. We believe for two reasons that the perspective that should be adopted is that of the NSFR. The first reason lies in the very definition of the LCR. It is defined as the ratio of HQLA over runnable liabilities. The problem is that the very fact of defining some assets as HQLA could make those assets illiquid in the event of a crisis. This idea is what has been coined as the Goodhart's law based on a quotation from a paper by Charles Goodhart according to which "any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes" (Goodhart, 1975). Gambling financial stability on the definition of liquid assets is therefore dangerous. AAA securitized products were indeed deemed rather liquid before their market freezed. The second reason echoes the current concern of prudential regulators to take climate change into account (Bolton et al., 2020). To do so, financial regulation has to incentivize banks to invest in green assets in order to fill the green investment gap. Those assets are in general long-term assets. By constraining banks to invest in short-term liquid assets, the LCR could thus deter banks from investing in green assets. Consequently, such liquidity requirements are expected to have a negative impact on the access to finance of low-carbon sectors (Campiglio, 2016). Liquidity regulation should then focus more on the liability side than on the asset side of the balance sheet.

To summarize, banking regulation has evolved after the great financial crisis to tackle the new risks that materialized at the end of the 2000s. However, the current regulatory framework suffers from obvious flaws. In particular, too many rules are being implemented and none is perfectly well-designed. We think that they could all be replaced by a unique strong equity constraint that would be both more transparent and efficient. In addition, we think that such a constraint would not impede banks' activities. This twofold hypothesis is discussed in more detail in the next section.

3.2.2 Tested hypothesis

Higher equity requirements could achieve the objective of all the rules that have been presented in the previous section. Equity is indeed the best funding instrument to absorb losses and thus to make sure that failing banks will be bailed-in instead of bailed-out. As Admati et al. (2013) note it, equity indeed dominates convertible debt in this matter. Liquidity regulation aims at ensuring the consistency of banks' balance sheet by limiting maturity mismatch. Before the crisis, banks indeed strongly relied on very short-term financial instruments to fund longer-term assets, which exposed them to short-term liquidity risks (Acharya et al., 2011; Morris and Shin, 2016). Defining higher equity requirements would probably make it possible to reduce the maturity mismatch and thus to reduce the exposure of banks to liquidity risks without relying on a questionable definition of which assets are deemed highly liquid and which are not. In addition, it could incentivize banks to invest more in green assets and thus favor the transition towards a greener economy: banks that rely more on equity face a lower liquidity risk and are, therefore, more able to invest in longer term assets.

In this perspective, strong equity requirements appear as a better solution than the definition of liquidity ratios to ensure financial stability and as a better solution than bail-in standards to protect taxpayers from costly bailouts. Such requirements are moreover expected to have a positive impact on the funding of green projects. In this chapter, we start from the idea that equity indeed performs better than both bail-in standards and liquidity ratios in fulfilling their goals.

Starting from this idea, we inquire whether the arguments opposed by the banking industry to higher equity requirements are justified or not. The main argument against such requirements is that they would have a negative impact on the ability of banks to conduct their activities by impeding their performance. We aim at providing empirical evidence that the relationship could actually be the reverse. Since higher equity requirements reduce the probability that banks end up bankrupting, it is expected that better-capitalized banks are able to issue bonds at a lower cost. All in all the total funding cost of banks could decrease and their profitability thus increase. If this is indeed the case, nothing opposes the definition of higher equity requirements. This is the hypothesis that is tested in this chapter. To do so, we resort to RF regressions, which are presented in the next section.

3.3 Random forest regressions

3.3.1 Tree-based models and random forest regressions

As already mentioned in the introduction, RF regressions have several advantages over other econometric strategies, especially when it comes to considering a large number of explanatory variables. They indeed perform well out-of-sample (Hastie et al., 2009), and allow to capture non-linearities and interactions between variables.

The RF methodology (Breiman, 2001) is a supervised statistical learning method[5] issued from bootstrap aggregation (or bagging) techniques. Bagging consists of averaging results of multiple repetitions of the same experiment, which is itself characterized by a high variance and a low bias. Since boosting methods are more adaptive than bootstrap aggregation approaches, they are generally preferred. However, RF regressions are slightly different from bagging,[6] and their performance is often close to those of boosting (Hastie et al., 2009). Since RF regressions are computationally simpler to implement, they are generally preferred to boosting methods.

The main idea behind the RF method is to average a more or less large number of decision trees. A tree is built by partitioning the space of explanatory variables into regions, and then by predicting an output value through a simple model (like a constant). The M final regions (or leaves) of the tree $\{R_m, m \in [\![1, M]\!]\}$, are obtained *via* recursive binary partitions. At each split of features space, we choose

[5]The model is trained on a sub-sample of the dataset and then tested on observations that have not been included in the training sample. The supervised aspect of this approach is the fact that we impose to the model the variable it shall predict.

[6]RF method averages responses of trees like bootstrap aggregation does. The difference comes from the fact that trees are built on a randomly selected sample among the training data and features.

the variable for which the split gives the best fit of the output variable (or label). Once the tree is built, the label is predicted by a constant value in each final region, that is:

$$f(x) = \sum_{m=1}^{M} c_m I(x \in R_m), \tag{3.3.1}$$

where x is the explanatory variable, I is an indicative function that scores 1 when $x \in R_m$, M denotes the number of final leaves (final regions), and c_m stands for the predicted value of the explained variable y, in region m. Therefore, this method is a non-parametric estimation of the unknown function f. This function defines the true model: $y = f(x) + \epsilon$, where ϵ designates the error term. Based on a criterion minimization of the sum of squares (Hastie et al., 2009), the best $\hat{c}_m$ is given by the average (ave) of y_i in region R_m:

$$\hat{c}_m = ave(y_i | x_i \in R_m). \tag{3.3.2}$$

To this point, there are still two parameters to define, which are j and s, respectively, the splitting variable and point. They delimit the two half-planes wrote as: $R_1(j,s) = \{X|X_j \leqslant s\}$ and $R_2 = \{X|X_j > s\}$. Finding j and s is equivalent to solve the problem given by:

$$min_{(j,s)}[min_{c_1} \sum_{x_i \in R_1(j,s)} (y_i - c_1)^2 + min_{c_2} \sum_{x_i \in R_2(j,s)} (y_i - c_2)^2]. \tag{3.3.3}$$

Solutions for the inner minimizations are given by Equation (3.3.2). Replacing $c_{i,i \in [\![1,2]\!]}$ by $\hat{c}_m$ in expression (3.3.3), the determination of s for each feature is deeply simplified. The selection of (j, s) is made comparing the results of the minimization problem given in (3.3.3) for every input variable. Once the two regions are identified, the process is repeated among them. As mentioned, RF, as proposed by Breiman (2001), aggregates the results of several trees that are built using a different bootstrap sample of the data (as bagging methods). This procedure allows considering different split points and various first splitting variables from one tree to another. This ensures results' convergence and that the complexity of the relationships involved is captured. In addition, Breiman (2001) suggests to change each tree's structure: the features selected in the process of a tree building are not necessarily the same from one tree to another. This ensures the de-correlation between trees. Therefore, parameters (j, s) for any given node are not the same between trees.

A second step in building a decision tree is to determine the maximum depth of a tree and the minimum number of observations in every leaves. Indeed shallow trees are likely to have poor prediction performance, and too deep trees might lead to overfitting issues and consequently bad out-of-sample forecasting. Following the same logic, a large number of observations per final region will predict poorly, while too little observations per leave are also subject to overfitting problems.
Thus the determination of those two parameters (depth and observations per leave) is crucial and can be done in various ways. In the context of a single tree, Hastie et al. (2009) propose to rely on a cost complexity criterion that should be minimized. This procedure works on the fact that an increase in complexity

(measured by the depth of the tree) that leads to overfitting the data and decreases the sum of squares is counterbalanced by an increase in a cost term that depends on the tree's depth. In the context of RF, this approach is quite demanding in terms of calculation: the criterion must be minimized for each tree. Another technique consists in making varying those two parameters in multiple RF regression estimations simultaneously and retain those that maximize the out-of-sample prediction performance.

The last parameter to establish is the number of trees in the forest. There are some debates on the optimal value for this parameter (and the very existence of an optimum). Hastie et al. (2009) suggest that the error of the model generally decreases and converges as the number of trees grows. From this perspective, the right number of trees corresponds to the moment where the error does not decrease below a certain threshold. Oshiro et al. (2012) show that, in some cases, the convergence of errors is not ensured. To avoid any risks in our empirical investigation, we determine simultaneously all three parameters: $(T_{max}, O_{min}, M_{trees})$, respectively the maximum depth of trees, the minimum number of observations per final region, and the number of trees. To do so, we compare RF regressions out-of-sample scores making those three parameters vary.

3.3.2 RF interpretation

As the number of features increases, visualization becomes more complex. However, it remains central since it often appears that numerous variables are irrelevant. This part is managed by the calculation of predictors' relative importance (Breiman et al., 1984; Hastie et al., 2009). Moreover, some techniques known as quantitative input influence make it possible to visualize features' impact on labels. Precisely, we use both Partial Dependence Plots (Friedman, 2000; Hastie et al., 2009) and Accumulated Local Effects (Datta et al., 2016).

In order to assess variables' importance, we rely on a generalization of Breiman et al. (1984)'s measure of relevance for a single tree:

$$\mathcal{I}_j^2 = \frac{1}{K}\sum_{k=1}^{K}\sum_{t=1}^{No-1} i_t^2 I(v(t) = j), \tag{3.3.4}$$

where $\mathcal{I}_j^2$ is the importance of the predictor variable X_j, K represents the number of trees in the forest, No indicates the number of nodes in the tree, $v(t)$ is the variable chosen at node t to split the space, and i_t^2 refers to the improvement gave by the splitting variable, in squared error risk compared to a constant adjustment across all regions. This measure attributes a score to all features giving their determining power on labels.

A Partial Dependence Plot (PDP) is then built to provide a summary of the output dependence on the joint values of the inputs (Friedman, 2000; Hastie et al., 2009). Considering a subset of $l < p$ inputs $X_{S,S\subset\{1,2,...,p\}}$ of $X^T = (X_1, ..., X_p)$, such that $f(X) = f(X_S, X_{S^C})$,[7] the partial dependence of f to X_S is given by:

$$f_S(X_S) = E_{X_{S^C}} f(X_S, X_{S^C}). \tag{3.3.5}$$

[7] S^C being the complementary of S: $S \cup S^C = \{1, 2, ..., p\}$.

Note that Equation (3.3.5) defines a measure of X_S effect on $f(X)$ after accounting for X_{S^c} effect. To calculate this impact in practice, we proceed as follows. We first assess Individual Conditional Effect (ICE), meaning the partial dependence of $f(X)$ on X_S when considering values of X_{S^c} for a given individual i:

$$ICE_i = \{\hat{f}(x_S^k, X_{i,S^C}), x_S^k \in [X_S^{min}, X_S^{max}]\}, \tag{3.3.6}$$

where ICE_i is the ICE for the i-th individual, X_{i,S^C} refers to values of X_{S^C} of this individual, and x_S^k are the values of X_S that vary from its minimum to its maximum with a step k. This provides a set of points representing a plot of partial dependence of the explained label on the variables included in S for the i-th individual. In a second step, we average those plots for all the individuals, and we obtain the PDP.

One of the most important issues in PDPs is that they assume independence between the predictor for which the partial dependence is computed and the other one. Besides, making x_S^k vary across all the distribution of X_S creates a risk to overfit regions with almost no data. In order to overcome this issue, we rely on Accumulated Local Effect (ALE).

ALE (Datta et al., 2016) also proposes to calculate the marginal effect of X_S. The main differences with PDP can be summarized as follows: ALE is unbiased even when features are correlated, it marginalizes over probable combinations of features, and it is faster to compute. Technically, ALE bases its calculation on existing data intervals for explanatory variables. Moreover, ALE averages the changes of predictions, not the predictions themselves. Another significant difference with PDP is that ALE accumulates the local gradients over the range of features S, giving their effect on the predicted variable. Finally, ALE method is centred so that the average effect is zero.

In practice, ALE for one given feature is computed, dividing it into many intervals, and computing the differences in the predictions.[8] First, the uncentred effect is calculated:

$$\hat{\tilde{f}}_j(x) = \sum_{k=1}^{k_j(x)} \frac{1}{n_j(k)} \sum_{i:x_j^{(i)} \in N_j(k)} [f(z_{k,j}, x_{\setminus j}^{(i)}) - f(z_{k-1,j}, x_{\setminus j}^{(i)})], \tag{3.3.7}$$

where $\hat{\tilde{f}}_j(x)$ is the uncentred effect of the variable j. $f(z_{k,j}, x_{\setminus j}^{(i)})$ gives the prediction given by the model, and considers the i-th individual for features values excepted x_j that takes the value $z_{k,j}$. The z are the values taken by the variable X_j that has been distributed on a grid defined by a given step. The internal sum adds up the impacts of all individuals within an interval $(i : x_j^{(i)} \in N_j(k))$ that appears as a neighbourhood. This sum is weighted by the number of individuals $n_j(k)$ present in the k-th neighbourhood. Finally, we sum the average effect over all intervals.

Second, we center in order to obtain a null main effect:

$$\hat{f}_j(x) = \hat{\tilde{f}}_j(x) - \frac{1}{n} \sum_{i=1}^{n} \hat{\tilde{f}}_j(x^{(i)}) \tag{3.3.8}$$

[8] This approximates the local gradients and allows us to compute ALE using RF regressions.

$\hat{f}_j(x)$ is interpreted as the main impact of the explanatory variable compared to the average prediction of the data.

From a practical point of view, some comments should be made. We use the sickit-learn package for RF regressions that includes PDPs calculation. ALE being a far more recent technique, it has not been widely developed yet. In our empirical analysis, we rely on the ALE-python package.[9] In the representation, we generally cut the extreme values of the variable we look at; indeed, the deviation from a value to another increasing as we move towards the distribution queues. As a result, the Quantitative Input Influence (QII) curves stretch for high values of the input and the additional information loses in relevance.

3.4 Data and descriptive statistics

3.4.1 Data

The objective of our empirical strategy is to determine what are the main predictors of banks' performance to decide whether or not increasing equity requirements would have the negative impact put forward by the banking industry to oppose them. To do so, we selected four variables to account for banks' performance: the return on average assets (ROAA) (Berger et al., 1995; Osborne et al., 2012; Tran et al., 2016; Xu et al., 2019), the return on average equity (ROAE) (Berger, 1995; Osborne et al., 2012; Distinguin et al., 2013; Tran et al., 2016; Xu et al., 2019),

[9] Note that this package includes Monte-Carlo simulations. Therefore, we provide the robustness checks consisting in assessing the average results over a 100 RF, only on PDPs.

the operating profit before tax to total assets (OPTA) (Xu et al., 2019),[10] and the net interest margin (NIM) (Albertazzi and Gambacorta, 2009; Xu et al., 2019).

Explanatory variables and the corresponding data sources are presented in Appendix 3.A. Among those variables, three are worth pointing out. The first one is equity over total assets ($\frac{\mathrm{E}}{\mathrm{TA}}$). This variable accounts for the proportion of the asset portfolio that is funded through equity. The higher the ratio, the better the bank is capitalized. The main purpose of our empirical strategy is to assess to what extent this ratio impacts banks' performance and in which direction. Higher equity requirements would indeed translate into higher values of this ratio. The other variables worth pointing out are the total capital ratio (TCR) and the liquidity coverage ratio (LCR). They account for prudential regulation as it is currently implemented. Determining their impact on banks' performance would allow to disentangle which part of banking regulation (if any) does impede banks' activities, as it is argued by the banking industry.

We consider two different databases that both consist in banks' balance sheet variables from twenty one countries[11] selected for their economic proximity, the fact that Basel III is nearly at the same stage of implementation in these jurisdictions, and the availability of data. The difference between the two databases lies in whether they include the LCR or not. Data are annual and come from the FitchConnect database.

[10]Note that the usual variable here is Operating Profit in level. A size effect being strongly detected in our regressions, we controlled for this bias dividing Operating Profit by Total Assets.

[11]Belgium, Canada, China, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, the Netherlands, Norway, Poland, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States.

The main constraint associated with the implementation of RF regressions is that they cannot be carried out successfully if the database contains any missing value. Taking this constraint into account, our two samples are as follows: the sample that includes the LCR among the explanatory variables comprises 63 variables for 1221 observations,[12] while the sample without the LCR includes 62 variables for 15310 observations. Rearranging the databases to remove twin variables (i.e,. those with a very similar definition and measurement), we kept respectively 46 and 45 variables.[13] Note that since the LCR is specific to Basel III, the dataset that contains it covers only the 2012-2018 period, whereas the other dataset goes from 2000 to 2018.

The critical difference in the number of observations when forcing the dataset to contain the LCR comes from the fact that FitchConnect does not disclose any data for this regulatory ratio concerning US banks.

3.4.2 Descriptive statistics

Before presenting the results of RF regressions, we display some descriptive statistics on the explained variables' distribution and the features correlations. Figure 3.4.1 shows the distribution of our four profitability variables. As can be seen, the output variables are highly concentrated around their respective average. All four variables also display some outliers,[14] but RF regressions are robust to the presence of such observations. Indeed, each tree is built on a new randomly selected

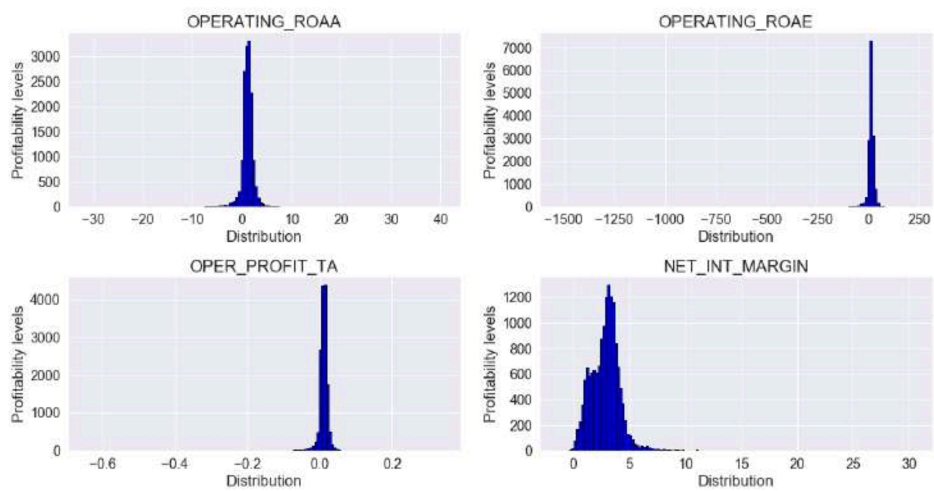
[12] An observation is defined as a bank for a given year. The number of banks evolves through the period we consider. See Appendix 3.B for more details on the number of banks.

[13] We also constrained the dataset to include some accounting and macroeconomic variables identified from the literature.

[14] Those outliers are not apparent being too few.

sample of features and data. Therefore, among the entire forest, outliers are taken into account.[15] As mentioned earlier, Partial Dependence Plots' calculation can be biased when features are correlated. As shown by Figure 3.4.2, which displays the linear correlations between all explanatory variables, high correlation exists for some features. Indeed, the sample of variables going from Business Volume to Other Assets displays high correlation levels with numerous other inputs. The use of ALE in order to support PDPs' results is thus relevant.

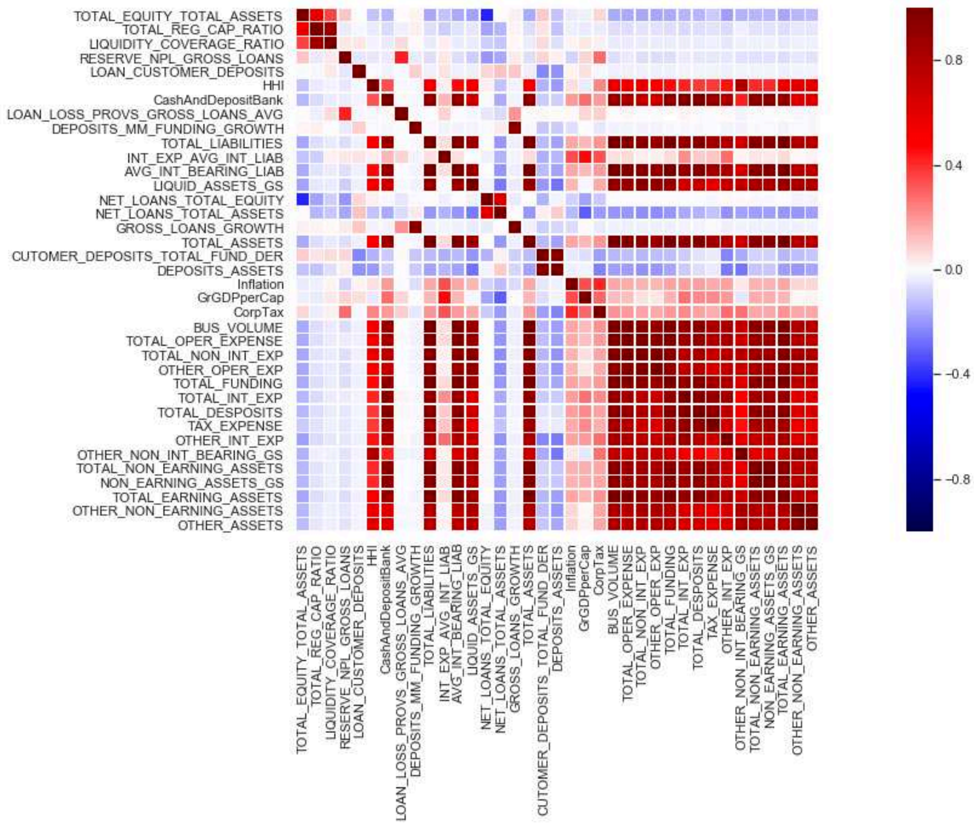
Figure 3.4.1 – Profitability variables' distribution



Source: Authors' calculations from FitchConnect data.

[15] To ensure that no bias is created by those high values, we constrained the sample selection of the robustness check by averaging results over 100 RF regressions. To do so, we forced the model to select data from all deciles. We controlled the sampling comparing the new and old distributions' first two moments. The goal of this robustness check is also to control for outliers in Lasso regressions.

Figure 3.4.2 – Linear correlation between features



Source: Authors' calculations from FitchConnect data.

3.5 Results of RF regressions

In this section, we present the results of RF regressions run on the sample that comprises the LCR when the ROAA and the ROAE are the dependent variables. Results concerning the OPTA and the NIM are in the Appendix 3.C.1 alongside with those run on the other sample. We first check the quality of the model by comparing its performance (as measured by the R^2) both in- and out-of-sample to those of the Lasso model[16]. We then present the main results regarding the

[16]The Lasso model (Tibshirani, 1996) consists in a shrinkage linear method for regression problem. It works imposing a penalty on the regression coefficients' size. Doing so, the model is forced to give importance to the coefficients that increase the most its quality.

ROAA and the ROAE.

3.5.1 RF *versus* Lasso model

A standard way to deal with a large number of explanatory variables is to resort to the Lasso model. Lasso indeed makes it possible to select among a great amount of explanatory variables those which are worth taking into account and those which are not. Inquiring what are the main determinants of banks' performance is therefore possible resorting to a Lasso model. However, in our case, RF regressions outperform the Lasso model. Running Lasso regressions on our dataset, we indeed notice that the R^2 of the RF model is always above that of Lasso models, whatever the dependent variable (Table 3.5.1). What is worth noting is that RF regression out-of-sample's R^2 is superior to those of Lasso model in-sample.

Table 3.5.1 Model's quality: RF versus Lasso

(a) ROAA as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.86	0.31	0.29
Out-of-sample	0.43	0.15	0.13

(b) ROAE as the dependent variable

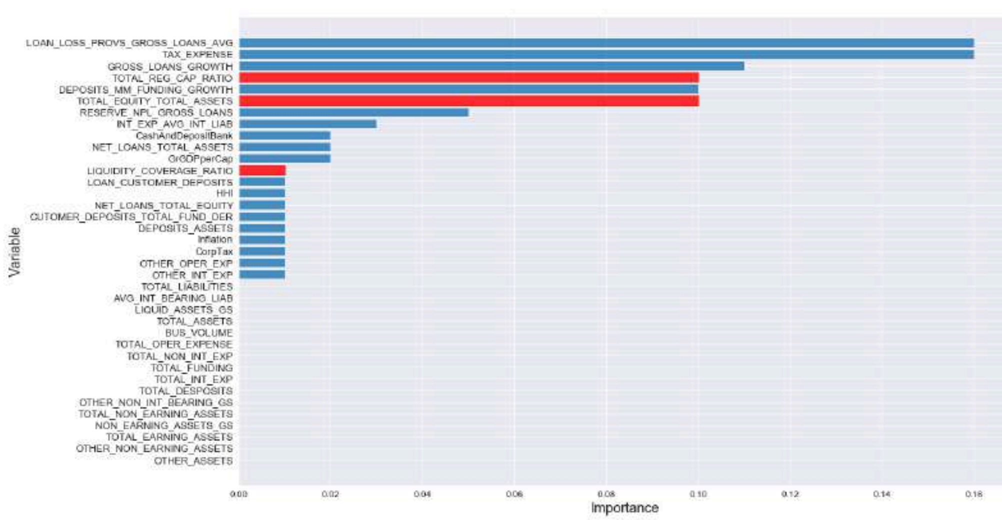
Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.81	0.24	0.21
Out-of-sample	0.56	0.09	0.10

Source: Authors' calculations. The table shows the coefficient of determination (R^2) scores. In the Lasso model, variables selection is done using both the Akaike information criterion (AIC) and the Bayes information criterion (BIC).

3.5.2 When $\frac{\mathbf{E}}{\mathbf{TA}}$ increases banks' profitability (ROAA)...

We report here the results of RF regressions when ROAA is the dependent variable. Figure 3.5.1 presents the importance of each explanatory variable in predicting ROAA. Few variables are identified as being strong determinants of bank activity's profitability. The ratio $\frac{\text{E}}{\text{TA}}$ is one of them, taking the fourth position of most important predictors. TCR is also associated with a great predictive power on ROAA. On the contrary, LCR is a poor predictor of ROAA and is therefore expected to have a weak impact.

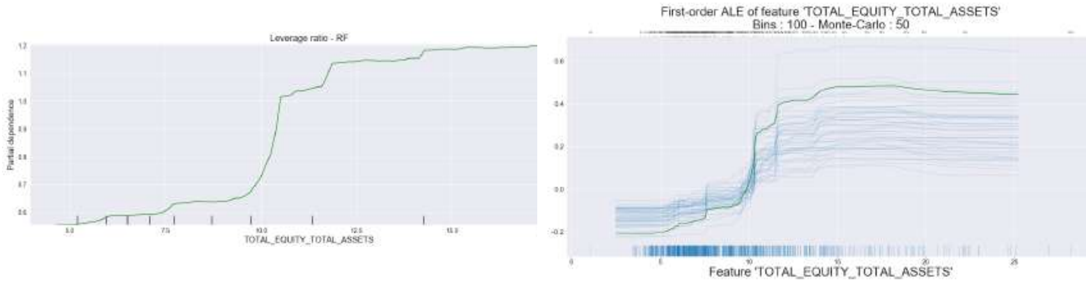
Figure 3.5.1 – Predictive power of each variable on ROAA



Source: Authors' calculations from FitchConnect data.

To determine in which direction goes the effect of the explanatory variables on ROAA, we use the PDPs and the ALEs. Results regarding the impact of $\frac{\text{E}}{\text{TA}}$ on ROAA are shown in Figure 3.5.2.

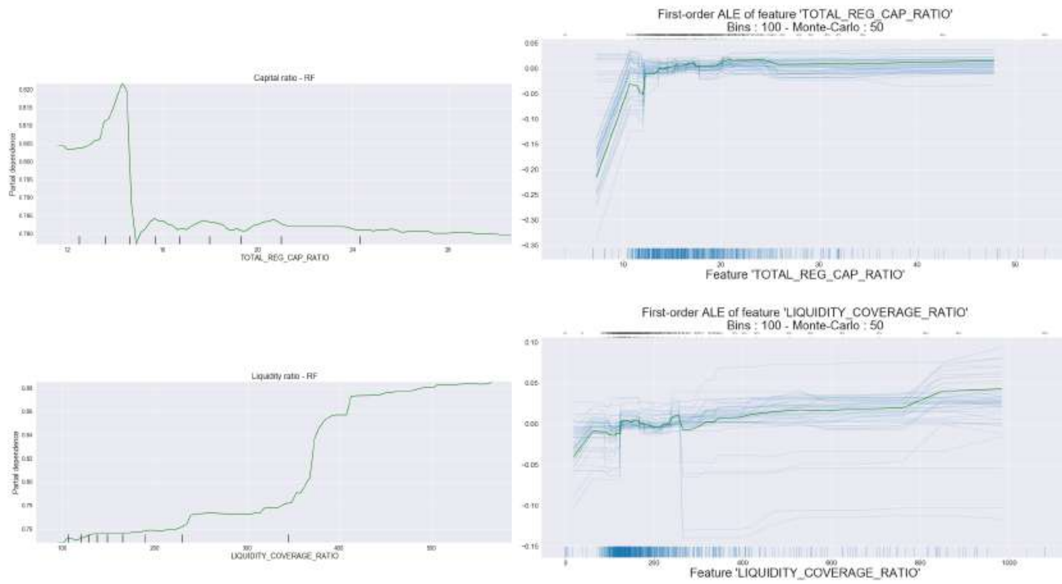
Figure 3.5.2 – Marginal impact of $\frac{E}{TA}$ on ROAA



Source: Authors' calculations from FitchConnect data. The left plot displays the PDP of $\frac{E}{TA}$, while the right plot shows the ALE. The distribution of $\frac{E}{TA}$ is reported on the x-axes (deciles and percentiles are displayed for, respectively, PDP and ALE).

We notice that $\frac{E}{TA}$ has a marginal positive and quasi-linear impact on ROAA. No matter the initial value of the ratio equity over total assets, increasing equity requirements would therefore have a positive impact on the performance of banks as measured by the ROAA. Higher values of $\frac{E}{TA}$ are associated with lower probabilities of default and therefore with lower funding costs. Banks whose funding structure strongly relies on equity thus face low funding costs, which allow them to perform well. In sum, looking at the impact of the ratio equity over total assets on banks' performance does not support the view according to which banking regulation hampers banks' activities. Let us consider the impact of regulatory variables (TCR and LCR) to assess whether this view can however be defended. Results are displayed in Figure 3.5.3.

Figure 3.5.3 – Marginal impacts of TCR and LCR on ROAA



Source: Authors' calculations from FitchConnect data. The upper plots display the PDP (left plot) and the ALE (right plot) of TCR, while the lower plots show the PDP (left plot) and the ALE (right plot) for LCR. The distributions of TCR and LCR are reported on the x-axes (deciles and percentiles are displayed for, respectively, PDP and ALE).

TCR has a non-linear impact on ROAA. Below a threshold value of approximately 16%, TCR has a positive impact on ROAA, while the effect is weakly negative (or even nil) for values of TCR lying above this threshold value. The idea according to which capital regulation could eventually have a negative impact on banks' performance seems to hold only for high capital ratios.[17] The marginal impact of LCR on ROAA is weakly positive. This is all the more true since we have seen that LCR takes the tenth place among ROAA's predictors.

TCR and $\frac{\mathrm{E}}{\mathrm{TA}}$ do not have the same impact on ROAA: the impact of TCR is strongly non-linear, while that of $\frac{\mathrm{E}}{\mathrm{TA}}$ is quasi-linear. That is quite surprising since those two variables both account for banks' capitalization. Recall however that TCR is defined as the ratio of regulatory capital (which includes both Tier 1 capital and

[17] I.e, for values above 16% which is higher than the sum of all capital requirements combined.

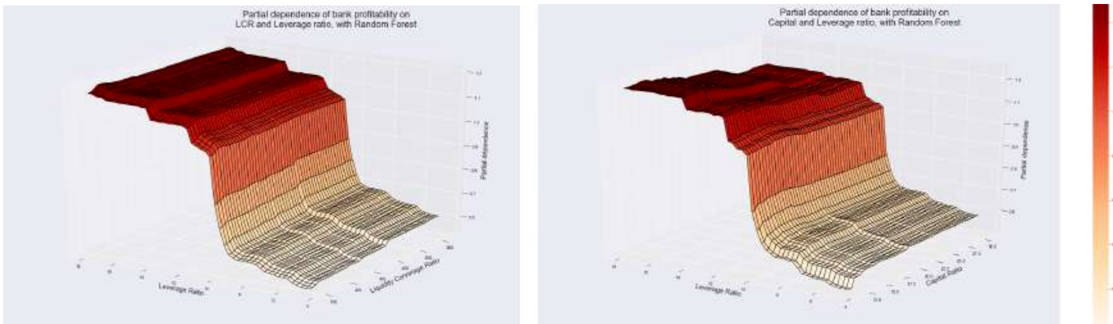
Tier 2) over risk-weighted assets, while $\frac{\mathrm{E}}{\mathrm{TA}}$ is the simplest capital ratio possible: the ratio of equity over total assets. What is thus to be learned from the results presented so far is that a simple capital regulation (based on a simple definition of capital and risk) never impedes banks' performance, while the sophisticated Basel III ratio does so for capital ratios above a certain threshold.

Figure 3.5.4 presents the effect of the interaction between $\frac{\mathrm{E}}{\mathrm{TA}}$ and the other regulatory variables (TCR and LCR) on ROAA. As for the marginal impact of each of these labels, we resort here to both PDPs and ALEs.[18] As was expected from Figure 3.5.1, the impact of $\frac{\mathrm{E}}{\mathrm{TA}}$ on ROAA is far stronger than those of TCR and LCR. Having for instance a look at the right plots, we indeed notice that the impact of the interaction between $\frac{\mathrm{E}}{\mathrm{TA}}$ and TCR on ROAA is entirely driven by $\frac{\mathrm{E}}{\mathrm{TA}}$. The same goes for the interaction between $\frac{\mathrm{E}}{\mathrm{TA}}$ and LCR.

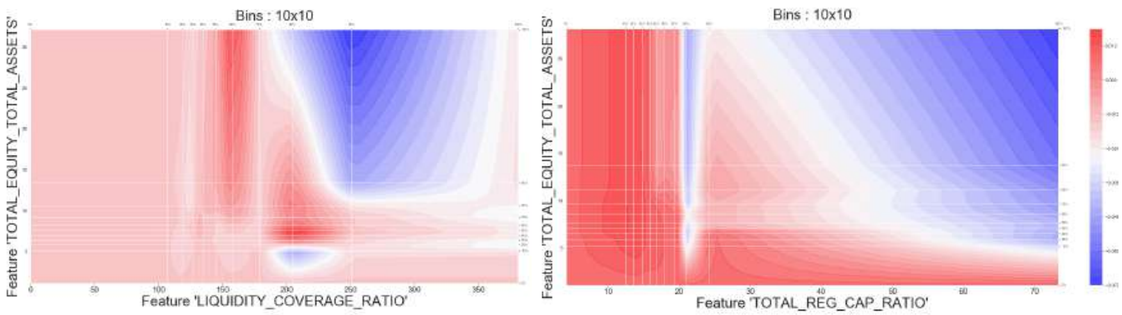
[18] As shown in Figure 3.4.2, those three regulatory variables are correlated with each-others. Therefore the use of ALEs is more relevant.

Figure 3.5.4 – Impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and regulatory variables on ROAA

(a) Two-ways PDPs of LCR with $\frac{\text{E}}{\text{TA}}$, TCR with $\frac{\text{E}}{\text{TA}}$



(b) Two-ways ALEs of LCR with $\frac{\text{E}}{\text{TA}}$, TCR with $\frac{\text{E}}{\text{TA}}$



Source: Authors' calculations from FitchConnect data. The left plots display the marginal impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and LCR on ROAA, while the right plots show the marginal impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and TCR on ROAA.

To summarize, $\frac{\text{E}}{\text{TA}}$ has a strong and quasi-linear positive effect on ROAA. On the contrary, regulatory variables have a weaker impact on ROAA and are thus less convincing determinants of banks' performance. The so-called negative impact of capital regulation on banks' activities is therefore likely to be very small when capital regulation is implemented through sophisticated ratios (such as TCR) and non-existent when it is designed as a much simpler ratio (such as $\frac{\text{E}}{\text{TA}}$). Finally, as shown in Figure 3.5.4, an optimal combination of LCR (or TCR) and $\frac{\text{E}}{\text{TA}}$ having a strong positive impact on ROAA and allowing compliance with regulatory requirements, can always be found.

Those results are supported by Lasso regressions run on the same sample (Table 3.5.2). The coefficient associated with the variable $\frac{\mathrm{E}}{\mathrm{TA}}$ is always significant and positive, while TCR and LCR are in both cases excluded from the model when variables' selection is done thanks to the BIC. When the AIC is used, the impact of TCR on ROAA is negative, which means that increasing TCR is expected to have a negative effect on banks' performance as measured by the ROAA. Once again, it is thus not capital *per se* that plays a negative role on banks' performance, but the complexity of the capital ratio (TCR *versus* $\frac{\mathrm{E}}{\mathrm{TA}}$). As for the impact of LCR on ROAA, it is here also very weak.

Table 3.5.2 Lasso regressions (ROAA as the dependent variable)

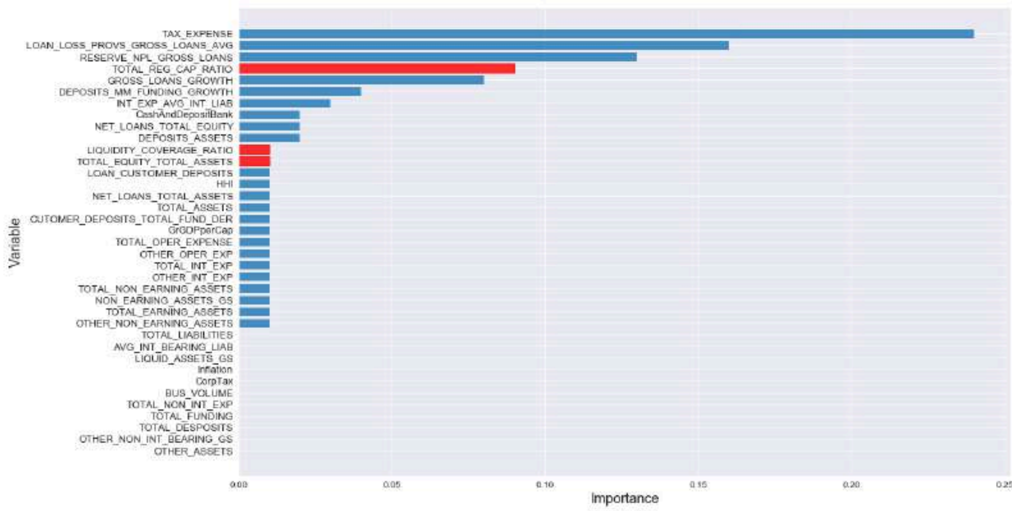
Variable	Models	
	Lasso (AIC)	Lasso (BIC)
$\frac{\mathrm{E}}{\mathrm{TA}}$	0.01169	0.0094
TCR	-0.0023	0
LCR	3.04 e-05	0

Source: Authors' calculations. ROAA is the dependent variable. Variables selection is done using both the Akaike information criterion (AIC) and the Bayes information criterion (BIC). A coefficient equal to 0 means that the variable has been excluded.

3.5.3 ... but has a negative marginal impact on shareholder value (ROAE)

In the previous section, we presented results supporting the idea that stronger equity requirements could have a positive impact on banks' performance when measured as the ROAA. This is in contradiction with the common wisdom, as put forward by the banking industry to oppose such strengthening of capital regulation. In this section, we resort to another measure of banks' performance (the ROAE) to try to make sense of this paradox. Figure 3.5.5 displays the predictive power of the explanatory variables on ROAE, in the RF regression.

Figure 3.5.5 – Predictive power of each variable on ROAE

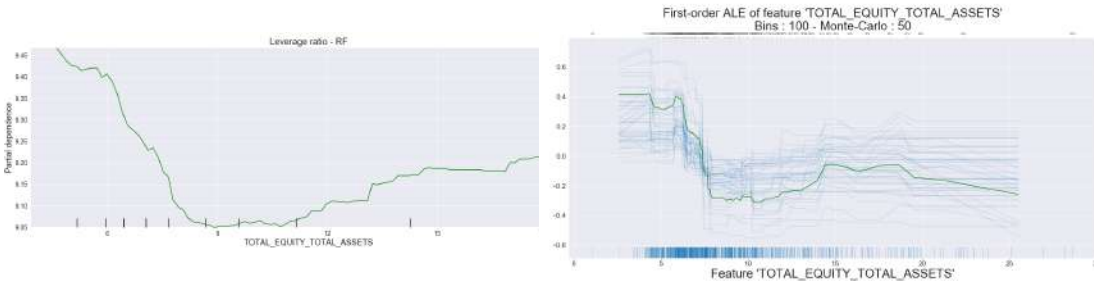


Source: Authors' calculations from FitchConnect data.

Here, TCR remains a strong determinant of profitability as measured by ROAE since it takes the fourth position among most important labels. On the contrary, $\frac{E}{TA}$ and LCR are both weak determinants of ROAE. Turning to the marginal impact of $\frac{E}{TA}$ on ROAE (Figure 3.5.6), we notice that increasing the value of this ratio is expected to have a negative impact on ROAE for values of this ratio below approximately 11%. For values of $\frac{E}{TA}$ above this threshold, the relationship is the other way round. Given that the majority of the banks in our sample lie before the value of $\frac{E}{TA}$ for which its impact on ROAE is positive (see the distribution on the x-axes), the impact of stronger equity requirements on the shareholder value is expected to be negative in the majority of cases. Having a closer look at the PDP (left plot in Figure 3.5.6), we indeed notice that 80% of the distribution lies in an area where the impact of $\frac{E}{TA}$ on ROAA is strongly negative or close to zero.

If banks seek to maximize their shareholder value, it is therefore in their interest to oppose stronger equity requirements.

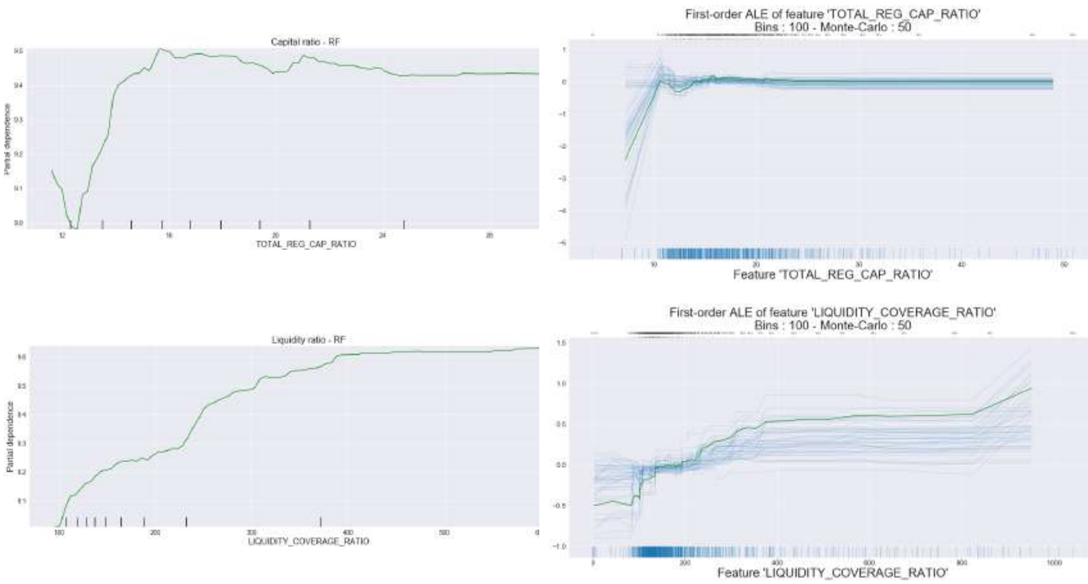
Figure 3.5.6 – Marginal impact of $\frac{\mathrm{E}}{\mathrm{TA}}$ on ROAE



Source: Authors' calculations from FitchConnect data. The left plot displays the PDP of $\frac{\mathrm{E}}{\mathrm{TA}}$, while the right plot shows the ALE. The distribution of $\frac{\mathrm{E}}{\mathrm{TA}}$ is reported on the x-axes (deciles and percentiles are displayed for, respectively, PDP and ALE).

Marginal impacts of TCR and LCR on ROAE are roughly the same as those on ROAA. Results are shown in Figure 3.5.7. TCR has a non-linear effect on ROAE: a positive impact below a threshold value of 16% and a negative or null impact above it. LCR has a positive impact.

Figure 3.5.7 – Marginal impacts of TCR and LCR on ROAE

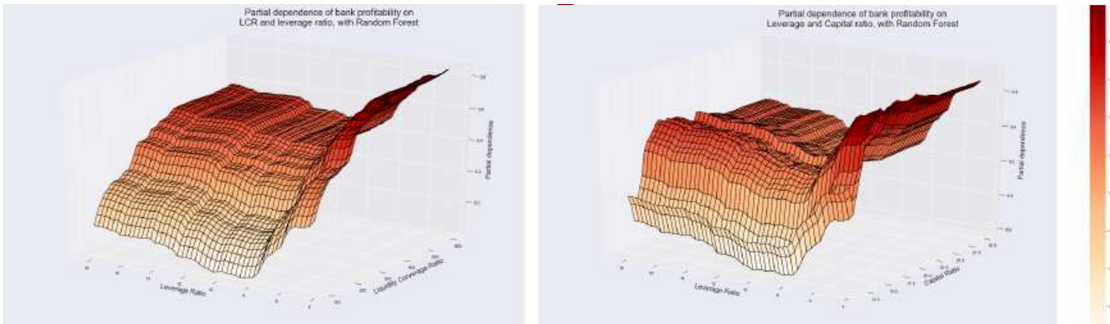


Source: Authors' calculations from FitchConnect data. The upper plots display the PDP (left plot) and the ALE (right plot) of TCR, while the lower plots show the PDP (left plot) and the ALE (right plot) for LCR. The distributions of TCR and LCR are reported on the x-axes (deciles and percentiles are displayed for, respectively, PDP and ALE).

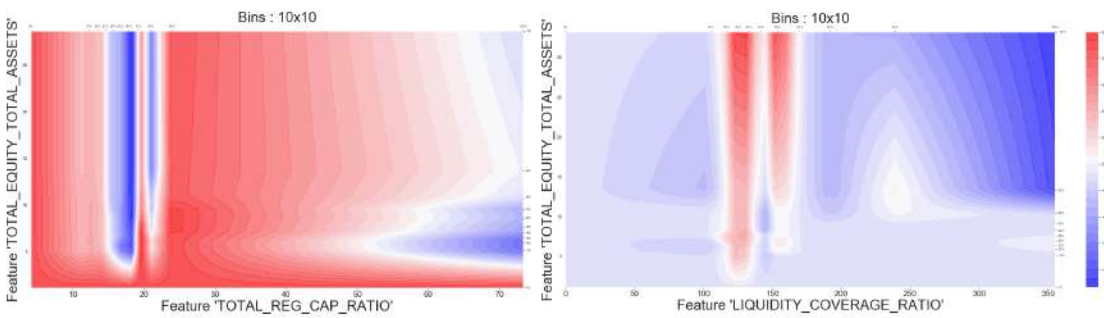
When we have a look at the impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and the regulatory variables on ROAE (Figure 3.5.8), we notice that it is in both cases mainly driven by $\frac{\text{E}}{\text{TA}}$. If banks want to maximize their ROAE, their best interest is to lobby for the implementation of a complex capital ratio instead of a simple leverage ratio. This is precisely the current shape of capital regulation: it is mostly designed around a complex capital ratio (which negative impact on ROAE is limited) while the regulatory leverage ratio is set at a very low level.

Figure 3.5.8 – Impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and regulatory variables on ROAE

(a) Two-ways ALEs of LCR with $\frac{\text{E}}{\text{TA}}$, TCR with $\frac{\text{E}}{\text{TA}}$



(b) Two-ways ALEs of LCR with $\frac{\text{E}}{\text{TA}}$, TCR with $\frac{\text{E}}{\text{TA}}$



Source: Authors' calculations from FitchConnect data. The left plots display the impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and LCR on ROAE, while the right plots show the impact of the interaction between $\frac{\text{E}}{\text{TA}}$ and TCR on ROAE.

To conclude, $\frac{\text{E}}{\text{TA}}$ has a negative but weak impact on ROAE. Implementing stronger equity requirements would therefore have an adverse impact on the shareholder value of banks. LCR also has a weak impact on ROAE. On the contrary, TCR has a strong non-linear effect on ROAE: a positive one below 16%, and a negative or null one above this threshold. If banks look at maximizing their shareholder value, they are, therefore, incentivized to oppose strong equity requirements to prefer instead much complex capital ratios. This is precisely how current capital regulation is implemented. Having a look at the impact of regulatory variables on ROAE, we therefore manage to formulate an explanation to make sense of the paradox mentioned at the beginning of this section. Despite the positive impact of the ratio equity over total assets on banks' performance when measured as the ROAA, it is likely that banks oppose equity requirements since they negatively affect their shareholder value.

Once again, Lasso regressions (Table 3.5.3) confirm the results drawn from RF regressions. They indeed show that $\frac{E}{TA}$ and LCR have a weak and negative impact on ROAE. TCR's impact is shown to be negative in those models. This is because the highest values of TCR influence the relationship between this variable and ROAE when captured through Lasso models.

Table 3.5.3 Lasso regressions (ROAE as the dependent variable)

Coefficient	Models	
	Lasso (AIC)	Lasso (BIC)
$\frac{E}{TA}$	-0.052	0
TCR	-0.028	-0.019
LCR	0	0

Source: Authors' calculations. ROAE is the dependent variable. Variables selection is done using both the Akaike information criterion (AIC) and the Bayes information criterion (BIC). A coefficient equal to 0 means that the variable has been excluded.

3.6 Robustness

3.6.1 Results for other profitability variables

To assess the robustness of our findings to the profitability measure, we use two other bank profitability variables (OPTA and NIM), and apply the same empirical approach as for ROAA and ROAE. The results are displayed in Appendix 3.C.1. The two models show high in-sample prediction performance, and higher out-of-sample R^2 than those of linear regressions in-sample (Table 3.C.1). The out-of sample explanatory power of RF regressions are 0.39% and 0.75%. These results corroborate those obtained with ROAA and ROAE: RF models have sufficient predictive power to be trusted. Regarding the most important variables (Figure 3.C.1), and the place taken by the three regulatory ratios among these, the results also confirm those of the regression with ROAA: $\frac{\text{E}}{\text{TA}}$ and TCR take prominent places, except for the TCR in the model with NIM, and LCR never appears as a powerful predictor of the model. For both OPTA and NIM, the marginal impact of $\frac{\text{E}}{\text{TA}}$ is positive and quasi-linear (Figure 3.C.2). Results of TCR on OPTA confirm those obtained with ROAA: the effect of TCR being positive before and becoming null or negative beyond the optimum. In the two models, LCR shows positive impact on profitability.[19] The interaction between $\frac{\text{E}}{\text{TA}}$ and profitability is confirmed in both models: the effect of the leverage ratio overcomes TCR and LCR impacts (Figures 3.C.3 and 3.C.4).

3.6.2 Results over 100 regressions

RF regressions are designed in a way that allows them to take into account the existence of outliers in variables' distribution. However, Lasso models are not. Besides, in order to evaluate models' out-of-sample quality, we randomly selected 75% of our datasets. Therefore, and to be sure that all the data are taken into account, we run 100 RF regressions and Lasso models forcing the data selection to over all deciles, and average the results. Doing so, we intend to confirm the

[19]PDPs and ALEs are not displayed here but are available upon request to the authors.

superiority of RF quality over Lasso models insuring that out-of-sample R^2 remain higher even when accounting for outliers. In all cases, RF regressions are more adapted than linear models.

3.6.3 Results in the large sample over 50 regressions

We assess the validity of our results regarding the leverage and capital ratios. We aim to confirm the nature of the relation between those two regulatory requirements with profitability variables. To do so, we run RF regressions on our four profitability variables using a dataset of more than 15 000 observations.[20] To ensure the stability of our results, we average outcomes of 50 RF regressions. The results of those regressions are displayed in Appendix 3.C.2.

As shown, models' quality remains high (Table 3.C.2). The importance and positive impact of $\frac{\mathrm{E}}{\mathrm{TA}}$ on ROAA, OPTA and NIM is confirmed (Figures 3.C.5 and 3.C.6). A negative effect of this ratio on ROAE is detected when looking at this sample, but for high values of ROAE (Figure 3.C.6). The non-linear impact of TCR (positive below 16% and then negative) is confirmed in all models except for the one with profitability as measured by the NIM.[21]

[20] Note that this robustness check also allows us to confirm our results on US banks and a larger period (2000-2018).

[21] Due to space constraints, we did not displayed those results but they remain available on request.

3.7 Conclusion

Banking regulation currently faces multiple challenges: mitigating the specific risk associated with banking activities and allowing the transition towards a greener economy. Those objectives are not easy to deal with, and it is very tempting to define one rule per problem to solve. This is what has been done in the recent years: the solvency risk is dealt with through risk-based capital ratios, the liquidity risk through liquidity ratios, and the cost associated with banks' failures through bail-in standards. Banking regulation is thus made of multiple complex rules, whose implementation is often arguable. In this chapter, we argue that another view on banking regulation could be adopted. Instead of the current multiplication of rules, we suggest implementing strong equity requirements. Such requirements would be simpler and more transparent than current rules, and would probably have a positive impact on the funding of long-term green assets.

Strong equity requirements are however opposed by the banking industry, arguing that they would impede too much banks' activities. Resorting to RF regressions and to numerous robustness checks, we show that the ratio equity over total assets has on the contrary a positive impact on banks' performance when measured as the return on assets. Far from impeding banks' performance, equity requirements could instead foster it. We also find that capital and liquidity requirements do not hamper ROAA, except for high values of capital. Furthermore, we show that the equity over total asset ratio's impact broadly exceeds that of TCR and LCR. However, the ratio of equity over total assets displays most of the time a negative impact on the shareholder value of banks. In sum, the cost associated with equity requirements is not a social cost (a reduction in banks' performance), but a private cost entirely supported by shareholders. There is therefore no economic reason to oppose to stronger equity requirements.

Our chapter also engages with the current debate surrounding the way financial regulation could tackle climate change. As famously put it by Mark Carney (Carney, 2015) financial regulation suffers from a "tragedy of horizons": it mainly focuses on short-term issues, while the time horizon of climate change is the long term. Breaking this tragedy requires extending the time horizon of both regulators and banks. Focusing on equity – which by definition is a stable source of funding – could allow to make one step in this direction.

Appendix

Appendix 3.A Data sources and definitions

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Table 3.A.1 Data sources and definitions

Data	Definition	Source
TOTAL REG CAP RATIO	Total regulatory capital ratio as defined under Basel agreements. It is fixed to 8% of the risk weighted assets, plus a conservation buffer (2%).	FitchConnect
LIQUIDITY COVERAGE RATIO	Short term liquidity ratio as define under Basel III agreements. Ratio of High Quality Liquid Assets to cash flow under stress.	FitchConnect
RESERVE NPL GROSS LOANS	Ratio of volume of NPL to gross loans. It gives a measure of credit risks took by a bank.	FitchConnect

Table 3.A.1 (continued)

LOAN CUSTOMER DEPOSITS	Loan to customer deposit accounts, which can be withdrawn on demand or short notice.	FitchConnect
LOAN LOSS PROVISION	Provision made by a bank to hedge against loan losses.	FitchConnect
LOAN LOSS PROVISION GROSS LOAN AVG	Ratio of loan loss provision to gross loans.	FitchConnect
DEPOSITS MM FUNDING GROWTH	Growth rate of deposits to money market funding.	FitchConnect
TOTAL EQUITY TOTAL ASSETS	Ratio of total equity to total assets. This ratio is close to the leverage ratio as defined under Basel agreements.	FitchConnect
TOTAL LIABILITIES	Liabilities of each bank.	FitchConnect
INT EXP AVG INT LIAB	Ratio of total interest expense / average interest-bearing liabilities.	FitchConnect
AVG INT BEARING LIAB	Average interest-bearing liabilities	FitchConnect
LIQUIDITY ASSETS GS	Liquid assets detained by the bank	FitchConnect

Table 3.A.1 (continued)

NET LOANS TOTAL EQUITY	Ratio of net loans to total equity.	FitchConnect
NET LOANS TOTAL ASSETS	Ratio of net loans to total assets.	FitchConnect
GROSS LOANS GROWTH	Growth rate of gross loans.	FitchConnect
TOTAL ASSETS	Total assets of the bank. Often used as a size proxy.	FitchConnect
CUSTOMER DEPOSITS TOTAL FUND DER	Ratio of customer deposits to total fund.	FitchConnect
DEPOSITS ASSETS	Money placed into banking institutions for safekeeping.	FitchConnect
BUS VOLUME	Managed Securitized Assets Reported Off-Balance Sheet + Other off-balance sheet exposure to securitizations + Guarantees + Acceptances and documentary credits reported off-balance sheet + Committed Credit Lines + Other Contingent Liabilities + Total Assets	FitchConnect

Table 3.A.1 (continued)

TOTAL OPER EXPENSE	Operating costs include administration costs such as staff costs.	FitchConnect
TOTAL NON INT EXP	Operating expense that is classified separately from interest expense and provision for credit losses.	FitchConnect
OTHER OPER EXP	Operating expenses.	FitchConnect
TOTAL FUNDING	Total Deposits, Money Market and Short-term Funding + Total Long Term Funding + Derivatives + Trading Liabilities	FitchConnect
TOTAL INT EXP	Interests on expenses costs.	FitchConnect
TOTAL DEPOSITS	Total deposits.	FitchConnect
TAX EXPENSE	Expense for current and deferred tax for the period.	
OTHER INT EXP	Interest expenses.	FitchConnect
OTHER NON INT BEARING GS	Non interest-bearing.	FitchConnect
TOTAL NON EARNING ASSETS	All assets that do not generate income.	FitchConnect

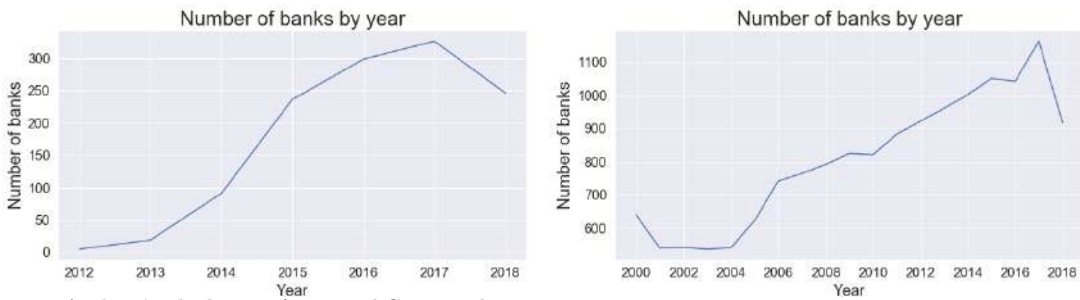
Table 3.A.1 (continued)

NON EARNING ASSETS	Assets that do not generate income.	FitchConnect
TOTAL EARNING ASSETS	All assets that generate income.	FitchConnect
OTHER NON EARNING ASSETS	Other assets that do not generate income.	FitchConnect
OTHER ASSETS	Other assets	FithConnect
HHI	Herfindahl-Hirschman Index. Gives a measure of the market concentration.	FitchConnect
CashAndDepositsBank	Cash and deposits from other banks.	FitchConnect
Inflation	Annual inflation rate.	OECD
GrGDPperCap	Annual GDP growth rate per capita.	World Bank
Corp Tax	Corporate tax rate.	OECD

Appendix 3.B Descriptive statistics

Figure 3.B.1 – Number of banks' evolution

(a) With LCR **(b)** Without LCR



Source: Authors' calculations from FitchConnect data.

Appendix 3.C Robustness outputs

3.C.1 Results for other profitability variables

Table 3.C.1 Model's quality: RF versus Lasso

(a) OPTA as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.85	0.24	0.22
Out-of-sample	0.39	0.15	0.14

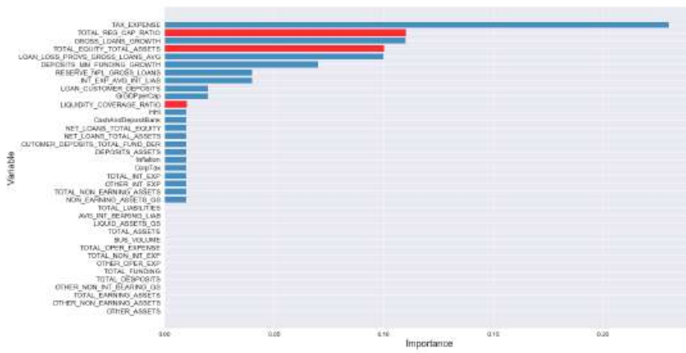
(b) NIM as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.92	0.48	0.47
Out-of-sample	0.75	0.42	0.41

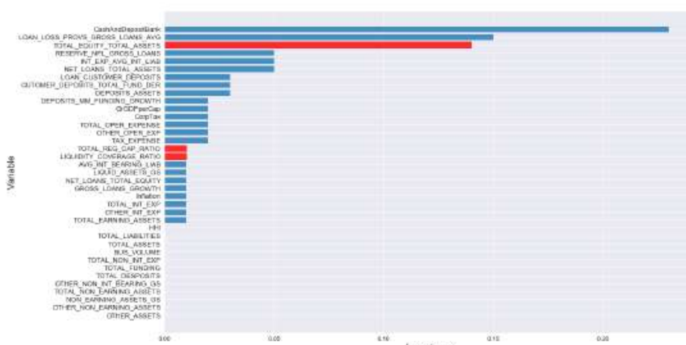
Source: Authors' calculations. The table shows the coefficient of determination (R^2) scores. In the Lasso model, variables selection is done using both the Akaike information criterion (AIC) and the Bayes information criterion (BIC).

Figure 3.C.1 – Variables' Importance - ROAE, OPTA, NIM

(a) OPTA



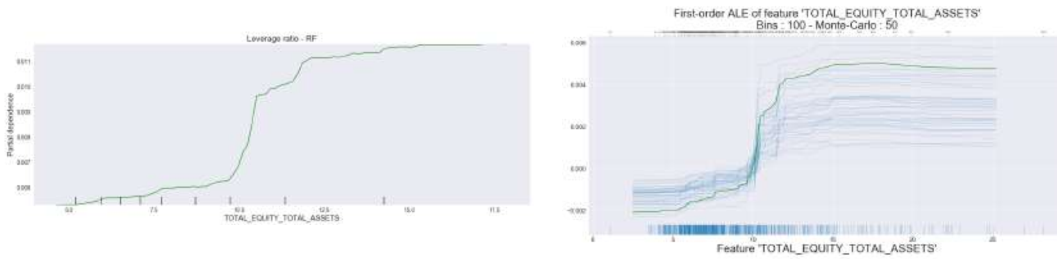
(b) NIM



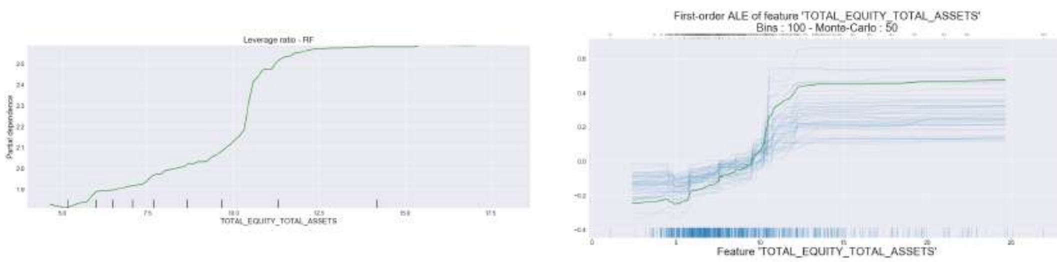
Source: Authors' calculations from FitchConnect data.

Figure 3.C.2 – PDPs and ALEs of $\frac{\text{E}}{\text{TA}}$

(a) Dependent variable: OPTA



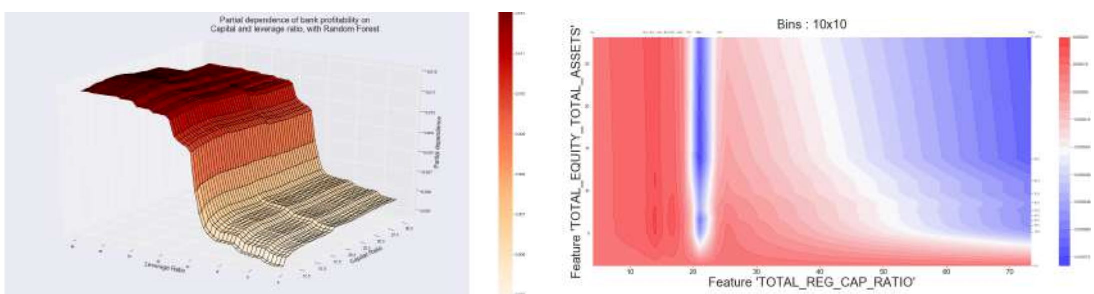
(b) Dependent variable: NIM



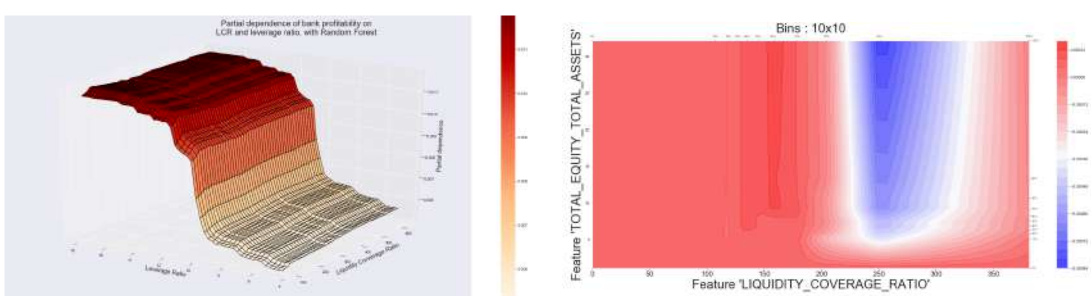
Source: Authors' calculations from FitchConnect data.

Figure 3.C.3 – Dependent variable: OPTA

(a) Two ways PDP and ALE - $\frac{\text{E}}{\text{TA}}$ and TCR



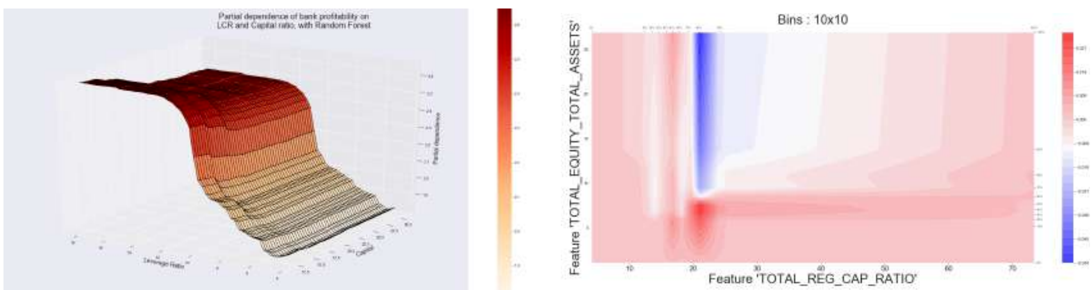
(b) Two ways PDP and ALE - $\frac{\text{E}}{\text{TA}}$ and LCR



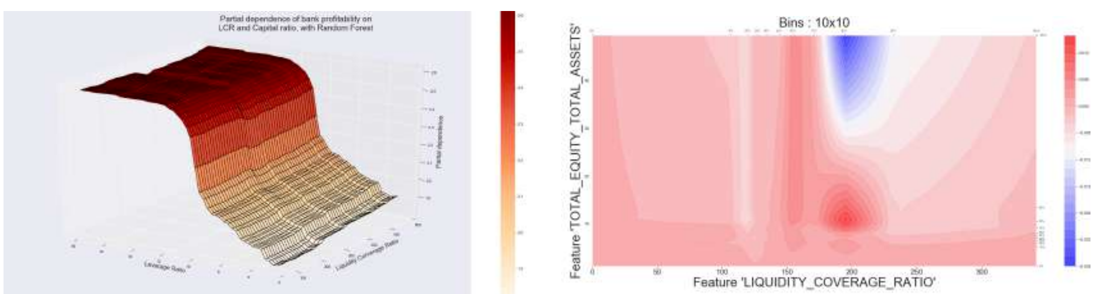
Source: Authors' calculations from FitchConnect data.

Figure 3.C.4 – Dependent variable: NIM

(a) Two ways PDP and ALE - $\frac{\text{E}}{\text{TA}}$ and TCR



(b) Two ways PDP and ALE - $\frac{\text{E}}{\text{TA}}$ and LCR



Source: Authors' calculations from FitchConnect data.

3.C.2 Results in large sample over 50 regressions

Table 3.C.2 Model's quality: RF versus Lasso

(a) ROAA as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.86	0.28	0.26
Out-of-sample	0.49	0.14	0.09

(b) ROAE as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.7	0.12	0.12
Out-of-sample	0.42	0.11	0.11

(c) OPTA as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.77	0.14	0.13
Out-of-sample	0.37	0.06	0.07

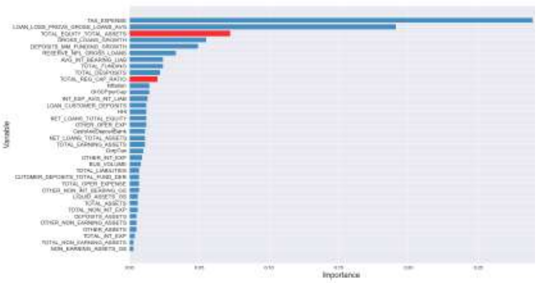
(d) NIM as the dependent variable

Sample	Models		
	RF	Lasso (AIC)	Lasso (BIC)
In-sample	0.85	0.37	0.36
Out-of-sample	0.67	0.36	0.36

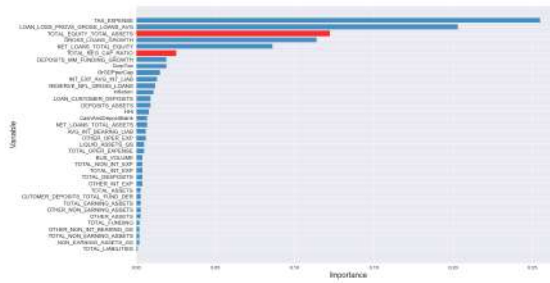
Source: Authors' calculations. The table shows the coefficient of determination (R^2) scores. In the Lasso model, variables selection is done using both the Akaike information criterion (AIC) and the Bayes information criterion (BIC).

Figure 3.C.5 – Variables' Importance in large sample - ROAE, OPTA, NIM

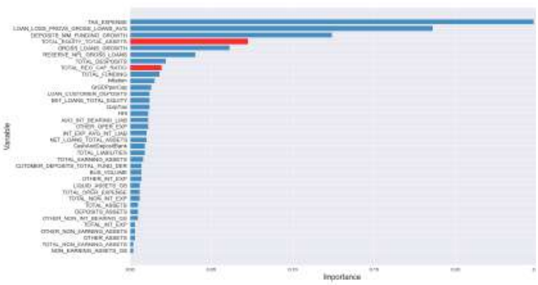
(a) ROAA



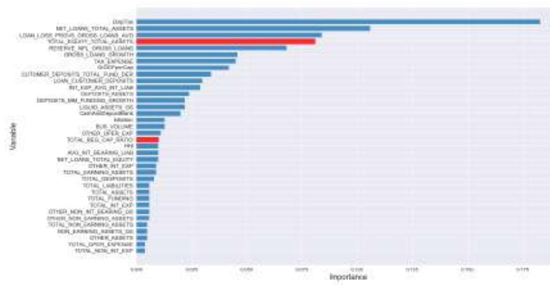
(b) ROAE



(c) OPTA



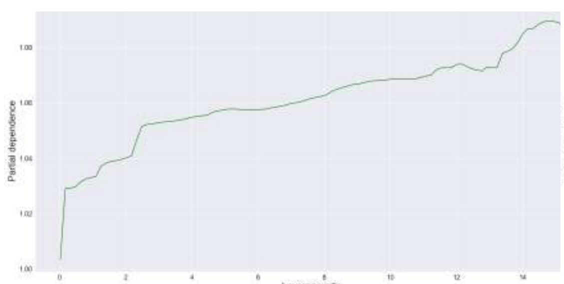
(d) NIM



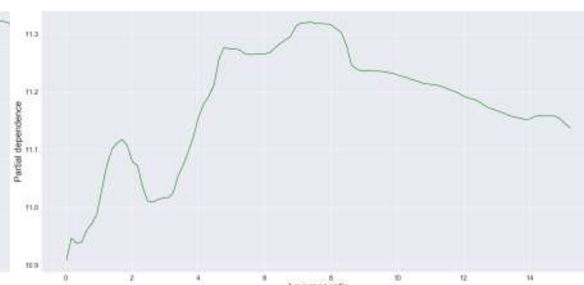
Source: Authors' calculations from FitchConnect data.

Figure 3.C.6 – PDPs of $\frac{E}{TA}$ in large sample

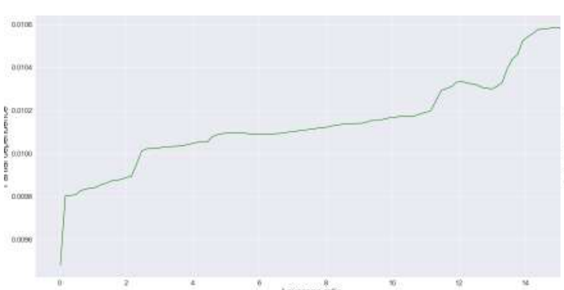
(a) ROAA



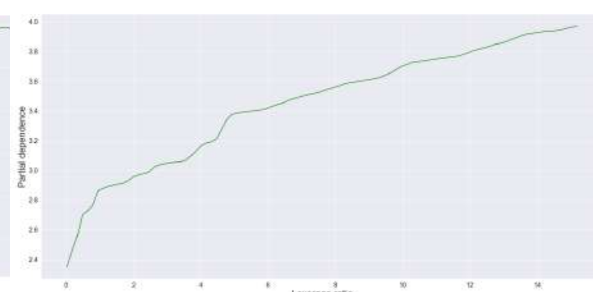
(b) ROAE



(c) OPTA



(d) NIM



Source: Authors' calculations from FitchConnect data.

Conclusion générale

L'occurrence d'une crise souligne les leçons qui n'ont pas été apprises de la dernière. "Cette fois, c'est différent", ou non, quoi qu'il en soit nous nous attelons à modifier les règles du jeu pour tenter de prévenir toute nouvelle dégénérescence du système. Bien souvent, une courbure de l'espace des risques s'opère et de nouvelles dérives ou perturbations apparaissent. C'est comme si Kitchin, Juglar et Kondratief détenaient la formule de l'univers. La crise de 2007-09 déroge-t-elle à la règle ? Elle nous a très certainement montré les faiblesses du système bancaire et financier dans lequel nous évoluions et d'importants remaniements prudentiels ont été menés en conséquence. Cette refonte des règles prudentielles suffira-t-elle à assurer la stabilité financière ? Le nouveau contexte réglementaire permettra-t-il de prévenir, ou tout du moins amoindrir les effets de la prochaine "purge" du système ? Les accords de Bâle III ont-ils résolu le "paradoxe de la tranquillité" ? Autant de questions auxquelles la crise sanitaire liée au Covid 19 risque malheureusement de répondre. Autant de questions auxquelles cette thèse ne répond pas. Ou presque. En effet, **nous menons dans cette thèse une analyse de l'efficacité réglementaire à plusieurs niveaux : au plan macroéconomique d'une part, et au plan**

microéconomique d'autre part. Nous abordons cette problématique en évaluant à la fois l'efficacité règlementaire du point de vue de ses objectifs et des dommages collatéraux éventuels qu'elle peut produire. A ce titre, nous apportons un certain nombre de réponses aux enjeux identifiés en introduction.

Le cadre réglementaire défini par les recommandations de Bâle III attache un intérêt particulier à la dimension macroprudentielle. Alors que les accords prévalant avant la crise de la fin des années 2000 tentent de renforcer la stabilité financière *via* l'instauration de règles établies à un niveau microéconomique, le corpus règlementaire récent, en plus de durcir et compléter les exigences micro-fondées, incorpore une perspective macroéconomique. Le premier chapitre de cette thèse a pour objectif d'évaluer l'efficacité de cette dernière en répondant à la question : d'un point de vue macroéconomique, la réglementation de Bâle III a-t-elle un impact positif sur la stabilité financière ? Le premier chapitre constitue donc une première contribution à la littérature existante. En effet, dans la mesure où il n'existe pas d'agrégat consensuel et reconnu pour mesurer la stabilité financière, nous proposons dans un premier temps, une approche construire pour un indicateur de stabilité financière. Dans un second temps, nous menons une analyse des effets des ratios prudentiels de capital et de liquidité sur cet indicateur.

Nous construisons un indicateur de stabilité financière (FSI) au niveau national pour 23 pays, sur la base de 12 variables macroéconomiques identifiées par la littérature comme représentatives de la stabilité financière. Pour obtenir le FSI, nous agrégeons ces variables en recourant à une analyse en composantes principales. Ce faisant, nous pouvons ensuite tester l'efficacité macroéconomique des règles prudentielles en estimant les impacts individuels et cumulés des ratios de capital et de liquidité sur le FSI. Nos résultats mettent en évidence l'existence de non-linéarités dans l'impact des ratios de capital et de liquidité sur la stabilité financière. Ainsi, l'effet d'une augmentation de l'un de ces ratios dépend à la fois de son propre niveau et de celui des autres ratios. Ce résultat constitue un apport à la thématique de l'évaluation de l'efficacité de la règlementation : il est nécessaire de prendre en compte les non-linéarités dans l'impact des règles et leur effet cumulé potentiel. Cela permet à la fois d'optimiser le niveau des exigences règlementaires et de mieux saisir les interconnexions entre ces exigences. Ce chapitre apporte également une contribution à la littérature existante dans la mesure où il souligne l'importance pour les régulateurs de se doter des outils nécessaires à l'évaluation de l'efficacité des politiques prudentielles. En outre, la constitution d'un indicateur de stabilité financière nous parait primordial.

Le premier chapitre s'intéresse à l'efficacité règlementaire sur un plan macroéconomique, évaluant ainsi l'un des aspects novateur et central de la règlementation de Bâle III : la règlementation macroprudentielle. Cependant, comme spécifié en introduction de cette thèse, les accords bâlois sont principalement axés sur des exigences micro-fondées. Par conséquent, une étape centrale dans l'évaluation de l'efficacité de la règlementation est de procéder à l'analyse et l'évaluation de l'impact des exigences sur un plan microéconomique. C'est précisément l'objet des chapitres 2 et 3.

Dans le deuxième chapitre, nous évaluons l'effet des ratios de capital, de levier et de liquidité sur la probabilité de défaut des banques. Nous nous basons sur des données bilancielles de plusieurs milliers de banques, 454 défauts aux Etats-Unis, et 207 défauts en Europe sur la période 2000-2018. A l'aide de modèles de classification de type logistique, forêts aléatoires et réseaux de neurones, nous sommes en mesure d'estimer la probabilité de défaut des banques, ainsi que l'importance prédictive des ratios prudentiels et leur impact sur cette probabilité de défaut. Nos résultats sur l'échantillon des banques américaines montrent très nettement que, au delà de la rentabilité mesurée par le rendement des actifs moyens, les ratios de capital et de levier sont prédominants dans la prédiction du défaut. Nous obtenons pour ces deux ratios, un impact négatif, ce qui est en accord avec l'intuition et la théorie économique. La liquidité affecte, en revanche, positivement la probabilité de défaut. Ce résultat contre-intuitif est à imputer au contexte de bas taux d'intérêt dans lequel notre étude s'insère. Dans l'ensemble, notre deuxième chapitre représente une contribution à la littérature existante pour plusieurs raisons. Premièrement, les études réalisées sur la probabilité de défaut s'attachent généralement à comparer la performance des modèles pour déterminer lequel est le plus pertinent pour ce type de problématique. Le choix de nous concentrer sur la réglementation comme prédicateur du défaut constitue donc une originalité.

Deuxièmement, nous confirmons l'idée selon laquelle l'accumulation de ratios n'est pas nécessaire : une règlementation basée sur un ratio de levier plus mordant serait au moins aussi efficace, quitte à ce que le ratio de solvabilité, très complexe, soit amoindri. Nous soutenons qu'une telle orientation de la politique prudentielle permettrait tout à la fois d'assurer une baisse de la probabilité de défaut des banques, diminuer la complexité du corpus règlementaire et pallier les risques du secteur bancaire de façon moins spécifique et donc plus intemporelle. Troisièmement, les modèles que nous estimons sur l'échantillon des banques européennes montrent des performances prédictives bien moins grandes. S'il est possible que ces résultats soient dûs à une différence fondamentale dans les déterminants du défaut entre les banques américaines et européennes, nous pensons que la qualité de la liste des banques ayant fait défaut en Europe n'est pas satisfaisante. En réalité, l'inexistence d'une liste officielle et publique des défauts en Europe pose un réel problème pour l'évaluation de l'efficacité de la transposition des accords de Bâle III en Europe.

Pour pouvoir acter la pertinence de notre proposition (axer la règlementation sur un ratio de levier plus élevé), et évaluer l'efficacité de la règlementation sous l'angle de ses dommages collatéraux potentiels sur l'industrie bancaire, nous procédons dans le troisième chapitre à l'estimation des impacts des ratios de capital, de levier et de liquidité sur la rentabilité des banques. Pour cela, nous avons recours à un large échantillon de banques européennes et américaines.

Pour pouvoir évaluer l'importance prédictive et le rôle déterminant des ratios prudentiels dans la formation du profit, nous implémentons les modèles Lasso et de forêts aléatoires. Par ailleurs, en plus des ratios règlementaires, nous incorporons dans notre échantillon des variables explicatives, un grand nombre de variables bilancielles. Nos résultats montrent que le ratio de levier est le ratio prudentiel prenant le plus d'importance dans la détermination de la rentabilité lorsque celle-ci est mesurée par le rendement des actifs. Par ailleurs, nous obtenons une relation positive entre le levier et la rentabilité. Enfin, il apparait que l'impact du ratio de levier outrepasse celui des ratios de capital et de liquidité. Ces résultats viennent confirmer le fait qu'une règlementation plus forte en levier ne constitue pas une contrainte pour l'activité des banques. Une contrainte apparait néanmoins sur la rentabilité actionnariale. En effet, un impact négatif du levier émerge lorsque l'on s'intéresse à la rentabilité telle que mesurée par le rendement des capitaux propres. Nous en déduisons que la ferveur avec laquelle l'industrie bancaire s'oppose à la mise en place d'un ratio de levier fort, n'est pas basée sur l'idée qu'une telle règlementation, en détériorant la rentabilité de l'activité des banques, porterait un coût social, mais un coût privé supporté par l'actionnariat bancaire.

Pour résumer, la règlementation en levier est efficace puisqu'elle peut s'avérer créatrice de "bénéfices collatéraux". L'exigence en capital fait apparaitre un optimum se situant autour de 15% et au delà duquel, elle peut devenir inefficace au sens où elle peut contraindre la rentabilité bancaire. La liquidité, malgré sa faible importance dans la détermination de la rentabilité, s'avère être efficace puisqu'elle ne produit pas d'effets non-désirés sur l'industrie bancaire. Enfin, le ratio de levier apparait plus efficace dans la mesure où son impact sur la rentabilité des actifs est à la fois positif et plus important que celui des deux autres ratios.

Ainsi, une contrainte en levier plus mordante que l'exigence actuelle de 3% diminuerait la probabilité de défaut des banques et aurait un impact positif sur la rentabilité bancaire mesurée par le rendement des actifs. En outre, favoriser le levier permettrait de clarifier une règlementation devenue trop complexe, et d'en faciliter l'évaluation de l'efficacité. Enfin, une contrainte plus forte en levier offre à la fois l'avantage de laisser moins de liberté d'optimisation interne et d'être plus intemporelle.

Un certain nombre de prolongements de nos travaux sont envisageables. De manière générale, la reproduction des études nous parait essentielle pour ancrer des résultats et confirmer leur validité. A ce titre, chacune des investigations que nous menons dans nos trois chapitres pourront être de nouveau menées à la lumière des événements liés à la crise sanitaire de 2020. Par ailleurs, la finalisation de Bâle III et la plus grande profondeur temporelle sur ces accords devraient permettre une évaluation de leur efficacité plus complète en intégrant, entre autres, plus d'observations sur les ratios de liquidité de court et de long termes. Du point de vue des prolongements en termes de politiques publiques, il est nécessaire d'incorporer de façon plus systématique la dimension environnementale dans les questions de l'efficacité règlementaire. Le fait que la thématique environnementale fasse partie intégrante des objectifs de règlementation doit être débattu.

Nous pensons que la mesure de stabilité financière proposée dans notre premier chapitre peut être précisée. De ce point de vue, une étude consacrée à l'élaboration d'un tel indicateur, prenant en compte les phénomènes de contagion, de réseau et de résilience, nous parait tout à fait pertinente.

Notre deuxième chapitre est au cœur de l'évaluation de l'efficacité microéconomique de la règlementation. Assoir les résultats que nous avons obtenus dans ce chapitre pour le cas européen constituerait une grande avancée sur le sujet. Pour cela, il est nécessaire de constituer une liste plus précise des défauts des banques que celles existant aujourd'hui. Plus encore, un grand nombre de banques se sont vues sauvées de la faillite par le biais de politiques publiques de renflouement ou de fusions et acquisitions. La mise au point d'une liste de ces banques pourrait préciser plus encore le travail d'estimation de la probabilité de défaut et de ses déterminants. D'un point de vue méthodologique, nous avons fait appel, dans ce chapitre, à des méthodes devenues standards pour ce type de problématique. Comme évoqué en Section 2.2, l'une des difficultés majeures dans le traitement de ce sujet tient de la rareté des événements observés de défaut. Le recours à des méthodologies propres à la détection d'anomalies pourrait constituer une approche novatrice et pertinente pour traiter ce sujet.

Enfin, le chapitre 3 s'intéresse aux dommages collatéraux éventuels des ratios prudentiels sur l'industrie bancaire. Pour mener cette étude, nous avons concentré notre analyse sur les impacts des exigences prudentielles sur la rentabilité des banques. Un prolongement pertinent de notre démarche dans ce chapitre consisterait en une investigation des dommages collatéraux de la règlementation sur le montant et les taux des crédits accordés par les banques.

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Liste des tableaux

Liste des figures

Efficacité de la règlementation prudentielle bancaire

Le retour du ratio de levier

Pierre Durand

2017-2020

A la suite de la crise financière de la fin des années 2000, une refonte importante et profonde de la réglementation prudentielle s'opère. De nombreuses limites et faiblesses du système financier et bancaire sont identifiées et il apparait essentiel de mettre en place un corpus de règles permettant d'y répondre. C'est dans ce contexte que s'inscrit l'élaboration des accords de Bâle III, qui posent les recommandations en termes de politiques prudentielles à l'ensemble des pays membres du Comité de Bâle (*Basel Committee on Banking Supervision*, BCBS). Un nombre important d'exigences réglementaires est alors mis en place dans les principales juridictions internationales. Cyclicité, quand tu nous tiens ! Douze ans plus tard et alors même que l'application des règles préconisées par ces accords n'est pas encore arrivée à terme, une première occasion de tester, en pratique, l'efficacité du nouveau cadre prudentiel se présente : la crise du Covid 19. Au moment où certains pays sortent à peine de leur période de confinement et où une incertitude plane quant à une recrudescence du virus, l'inéluctable impact économique de la crise sanitaire est encore difficile à évaluer. L'ensemble des acteurs de la sphère économique propose déjà un certain nombre d'évaluations des conséquences de la crise et de prospections de ses impacts sur l'ensemble très large des secteurs qui risquent d'être touchés[1]. Les régulateurs ne se seront pas fait attendre et mettent en place un assouplissement de certaines exigences réglementaires, notamment en capital et liquidité[2]. Même si la réactivité des instances de régulation envoie un signal plutôt positif, nous sommes en droit de nous poser la question : si le cadre réglementaire posé après la crise de 2007-09 doit permettre de solidifier le système financier et bancaire mondial, pourquoi l'assouplir à la première résurgence d'une crise ? La réglementation aura-t-elle été suffisante pour permettre au système bancaire d'être résilient face à la crise du Covid 19 ? De manière générale, **la réglementation bancaire a-t-elle un caractère assez intertemporel pour que le système bancaire puisse se remettre efficacement et rapidement de nouvelles éventuelles crises économiques ? C'est cet aspect d'efficacité que nous cherchons à questionner dans cette thèse.** Sans pouvoir assurer que les accords de Bâle III permettront, ou non, de prévenir les prochaines grandes perturbations économiques, nous proposons une approche pour en évaluer l'efficacité. Pour mieux comprendre notre approche et les différents angles que nous adoptons, nous revenons dans un premier temps sur la philosophie dans laquelle s'insère la réglementation bâloise et les raisons qui ont poussé les régulateurs à mettre en place les exigences qui prévalent aujourd'hui. De cette définition de notre cadre de travail, nous déduisons quelques enjeux et limites liés à la réglementation. Ces précisions nous permettent d'exposer le plan de notre thèse et la problématique à laquelle il répond : **sur les plans macro- et microéconomiques, la réglementation prudentielle se révèle-t-elle efficace et sans dommage collatéral pour l'industrie bancaire ?**

[1] Parmi d'autres études, nous pouvons citer les 35 bulletins publiés par la Banque des Règlements Internationaux.

[2] Voir, par exemple, le communiqué de presse du Parlement Européen du 19 juin 2020 sur l'assouplissement des règles en Europe pour faciliter le prêt bancaire.

1 Philosophie et définition de la réglementation

1.1 Principes généraux de la (nouvelle) réglementation prudentielle

Brossard et Cheitoui (2003), dans une analyse historique de la réglementation antérieure à 1945, soulignent que "la maturation de la réglementation prudentielle dépend de la façon dont les acteurs de la finance assimilent les leçons de la crise financière". C'était vrai pour la mise en place des exigences prudentielles nationales d'avant guerre, et ça l'est encore pour les trois accords internationaux établis à Bâle respectivement en 1988, 2004 et 2010.

C'est donc après une tendance importante à la déréglementation à l'issue des "30 Glorieuses" et après les perturbations des années 1970 qu'est d'abord créé le Comité de Bâle en 1974, avec pour objectif d'assurer la stabilité d'un système bancaire de plus en plus internationalisé (Goodhart, 2011), puis que les recommandations de Bâle I sont formulées, en 1988. Ces accords incitent les différentes juridictions à mettre en place un ratio de solvabilité minimum : le ratio Cooke, qui établit à 8% du total des actifs pondérés par les risques de crédit, le montant des fonds propres que les banques doivent détenir constamment[3].

C'est également après une crise, celle liée à la bulle internet du début des années 2000, que sont constatées certaines des faiblesses inhérentes à la réglementation en vigueur : la structure comptable du ratio de Cooke est trop axée sur le montant des crédits. Autrement dit, seul le risque de crédit est pris en compte. Or, les années 1990 voient les instruments financiers se diversifier, se complexifier et se sophistiquer, ce qui accentue les risques de marché et opérationnel, parallèlement à l'intensification de l'intrication des institutions financières au niveau international.

[3]Voir le texte original du Comité de Bâle : "International convergence of capital measurement and capital standards"

Les accords de Bâle II[4] viennent formuler de nouvelles recommandations : la définition des actifs pondérés par les risques est revisitée et prend en compte les risques de marché et opérationnel, un volet de surveillance prudentielle est mis en place, et l'idée d'une discipline de marché est intégrée *via* la mise à disposition publique des informations sur l'actif et la gestion des risques.

Cette structuration du cadre réglementaire en trois piliers est conservée lorsque, après la "Grande Récession" de 2007-09, le BCBS révise ses recommandations en termes de politique prudentielle pour donner lieu en 2010 aux accord de Bâle III[5]. De la même manière que pour les précédentes révisions du règlement prudentiel, pour comprendre la philosophie dans laquelle se place l'élaboration des derniers accords bâlois, il faut saisir les causes identifiées de la crise bancaire intervenue à la fin des années 2000. Bignon *et al.* (2018) dégagent trois principales causes de la crise qui sont aussi à l'origine des remaniements prudentiels : (i) la fragilité des institutions financières, (ii) le risque de contagion et (iii) l'opacité des transactions. Devant ce constat, pour prévenir le plus de risques possible et dans un souci d'exhaustivité, le nombre de ratios réglementaires a été démultiplié et leur composition (notamment celle du ratio de capital) s'est densément précisée[6] : la réglementation en capital a été réévaluée et redéfinie pour intégrer les risques de systémicité et de défaut, un ratio de levier est instauré, et deux ratios de liquidité sont introduits. Par ailleurs, des instruments de résolution interne ont été définis. Bâle III vise également à encadrer les pratiques de management, la systémicité des banques ou encore la discipline de marché. Au delà d'une évidente complexification du règlement prudentiel, discutée en Section 2.2, deux points nous paraissent importants dans la compréhension de la nouvelle réglementation. D'une

[4]Voir le texte original du Comité de Bâle : "Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version"

[5]Voir le texte original du Comité de Bâle : "Basel III: international regulatory framework for banks"

[6]Le détail de la réglementation de Bâle III est donné en Section 1.3

part, les préoccupations macroprudentielles y prennent une place prépondérante et, d'autre part, cette nouvelle règlementation est axée autour de l'idée de "un risque, une règle". Le premier point nous aidera à aborder l'évaluation de l'efficacité du cadre prudentiel actuel, et le second à façonner les recommandations en termes de politiques publiques que nous en déduisons.

1.2 Les différents objectifs de la réglementation

Afin de pouvoir mener une évaluation de l'efficacité de la réglementation, il est important d'en comprendre les objectifs. Si ces derniers sont remplis, on peut en déduire que la contrainte réglementaire fonctionne. Comme définie par la Banque Centrale Européenne, la régulation prudentielle bancaire est conçue pour accroitre la résilience des institutions de crédit et supporter la stabilité du système financier dans son ensemble[7]. Il s'agit d'un objectif clairement identifiable et simplement formulé. Déterminer s'il est atteint est autrement plus compliqué.

Les définitions et mesures de résilience et de stabilité financière sont en effet loin d'être triviales. Cette problématique fait l'objet d'une discussion dans la Section "Financial stability: survey and methodology for a composite indicator" de notre premier chapitre. Nous y dressons notamment le constat que la plupart des études réalisées par les instances de régulation sur la stabilité financière visent généralement un ou plusieurs secteurs clefs de la stabilité financière[8]. Il n'existe pas en revanche de mesure consensuelle de stabilité financière globale. Les préoccupations macroprudentielles sont pourtant prépondérantes dans la conception des accords de Bâle III[9] (Bennani *et al.*, 2017). Afin d'évaluer l'efficacité des règles prudentielles, il nous parait donc primordial de nous confronter à cette

[7]Maddaloni et Scopelliti (2019) : "Banking regulation and supervision are designed to increase the resilience of credit institutions and to support the stability of the financial system overall."

[8]C'est notamment le cas des rapports de stabilité financière (GFSR) proposés bi-annuellement par le Fond Monétaire International (FMI).

[9]Voir la Section 1.3 pour plus de détails.

question de la mesure de la stabilité financière et des impacts des règles bâloises sur elle.

Ainsi que nous le développons ci-après, les exigences réglementaires prennent avant-tout la forme de contraintes bilancielles adressées aux banques individuellement. Leur construction est donc principalement microprudentielle. De ce point de vue, l'objectif de la réglementation est, entre autres, de réduire le risque de défaut des banques.

Enfin, la régulation doit pouvoir s'appliquer sans contraindre l'activité des institutions. Brossard et Chetioui (2003) établissent d'ailleurs que la structure concurrentielle de l'industrie bancaire est un déterminant de l'efficacité prudentielle. Par ailleurs, la Banque Mondiale souligne l'importance de la compétitivité au sein du secteur bancaire dans la détermination de la stabilité financière (Allen *et al.*, 2009) : la perte de pouvoir de marché pourrait entrainer une fragilisation de la capacité des banques à générer du profit et, en conséquence, à prendre des risques. Si la réglementation contraint trop fortement les banques, un effet non-attendu pourrait être l'augmentation de la prise de risque et la fragilisation du secteur. Les effets de la réglementation sur le profit des banques, sont donc à prendre en compte lorsque l'on s'intéresse à l'efficacité de la réglementation.

1.3 Bâle III

Nous précisons brièvement ici la structure de la réglementation telle que recommandée par Bâle III. Nous nous arrêtons principalement sur les aspects de la réglementation qui nous intéressent pour cette thèse.

Comme évoqué ci-avant, les accords de régulation prudentielle bancaire de 2010 conservent la structuration en trois piliers, mise en place sous Bâle II :

- *Pilier 1* : ce pilier définit les exigences en capital[10].

[10]Puisque non traité dans cette thèse, nous n'évoquons pas ici certaines composantes de ce

– Le ratio de solvabilité, ou de capital, a pour objectif de renforcer la capacité d'absorption des pertes des banques. Bâle III préconise que le niveau des actions ordinaires (CET1) doit représenter 4,5% du montant des actifs pondérés par les risques (RWA). S'ajoute à ce seuil, un coussin de conservation à hauteur de 2,5%[11]. Le niveau minimum de capital dur est donc établi à 7% des RWA. En prenant en compte les contraintes en capital Tier 1 et 2, on obtient un seuil minimum pour le ratio de capital à 10,5% des RWA. Il faut ajouter à cela, un volant contra-cyclique pouvant varier de 0 à 2,5% des RWA en fonction du cycle. Enfin, une surcharge systémique est instaurée et peut varier de 0 à 3,5% des actifs pondérés par les risques. Au total et en fonction du cycle et du niveau de systémicité d'une banque, le ratio de capital requis peut varier de 10,5 à 16,5%.

– Bâle III introduit également un ratio de levier à hauteur de 3% : les fonds propres doivent représenter au moins 3% du bilan et hors bilan de la banque. Son objectif est de limiter un excès de financement par la dette. Ce ratio, bien plus simplement défini, permet en outre de diminuer la prise de risque (Bignon *et al.*, 2018) et d'être moins sujet aux modèles internes.

- *Pilier 2* : ce pilier encadre la procédure de surveillance de gestion des fonds propres et de prise de risque par le régulateur. Il veille donc à ce que les banques disposent des capitaux suffisants pour supporter les risques qu'elles endossent, et aient recours à des pratiques de gestion des risques saines. En outre, ce pilier concerne également les prises de risques liées aux expositions

pilier : le traitement de la titrisation, la gestion du risque de contrepartie, ou encore l'exposition des banques aux chambres de compensation. Sur ces derniers points, on pourra consulter la BIS : *The Basel Framework*

[11] Ce montant peut varier, notamment en période de crise, mais sous risque de se voir imposer des restrictions en termes de distribution de dividendes.

hors-bilan et de titrisation.

- *Pilier 3* : ce dernier pilier concerne les règles de publication des composantes des ratios réglementaires. Le pilier 3 encadre donc les contraintes en termes de discipline de marché.

Bâle III introduit également deux nouveaux ratios portant sur la liquidité. Le *Liquidity Coverage Ratio* (LCR) et le *Net Stable Funding Ratio* (NSFR).

- Le LCR, rapportant le montant des actifs hautement liquides (*High Quality Liquid Assets*, HQLA) au total des sorties de liquidité dans une période théorique de trente jours de crise de liquidité. L'objectif ici est de renforcer la capacité des banques à respecter leurs engagements en cas de crise de liquidité.

- Le NSFR établit que le montant des financements stables doit être supérieur au montant des financements nécessaires. Ce ratio est dit de long-terme et doit assurer la stabilité du financement des banques.

L'introduction de considérations macroprudentielles dans les accords de Bâle III passe donc par le coussin contra-cyclique et le coussin de systémicité, qui composent tous deux le ratio de capital. L'exigence en capital contra-cyclique varie en fonction du niveau de risque de bulle de crédit évalué par le régulateur. Comme précisé plus avant, il peut varier de 0 à 2,5% des actifs pondérés par les risques.

Le coussin systémique constitue une surcharge en capital pour les banques identifiées comme portant un risque pour l'ensemble du système en cas de défaut. L'objectif de cette règle est, entre autres, de limiter le paradigme du "Too Big To Fail". Le Bureau de Stabilité Financière (FSB), sur la base de cinq critères[12],

[12]La taille, le degré d'interconnexion avec d'autres institutions financières, leur degré de substituabililité, le niveau de leurs activités transfrontalières et leur niveau de complexité.

attribue une mesure de systémicité aux banques les plus importantes. En fonction de ce score (*Global Systemically Important Banks Score*) les banques les plus systémiques peuvent se voir attribuer une surcharge en capital.

Enfin, deux normes de résolution sont mises en place pour pallier la nécessité d'une intervention des pouvoirs publics en cas de perturbations : le *Total Loss Absorbing Capacity* (TLAC) et le *Minimum Requirement for own funds and Eligible Liabilities* (MREL).

2 Enjeux et limites

2.1 Spécificité et temporalité

Dans son discours sur les outils de politique macroprudentielle le 13 août 2014, Claude Borio, chef du département monétaire et économique à la Banque des Règlements Internationaux (*Bank of International Settelments*, BIS), évoque les lacunes des *stress tests* :

> "As early warning devices to identify vulnerabilities in tranquil times, they have so far proved woefully deficient. Their effectiveness is undermined by limitations of the modelling technology, not least the ability to capture sudden changes in behaviour, and by the context, not least the "this-time-is-different" syndrome. No macro stress test, in fact, identified the serious vulnerabilities that ushered in the financial crisis. While improvements have been made, there is a risk of putting too much faith in the tool's remedial properties."

Cette critique est applicable à l'ensemble des mesures réglementaires : au delà des contraintes en termes de modélisation technique, l'évaluation de l'efficacité des règles prudentielles se heurte à la difficulté qu'il y a de prendre en compte les changements de comportements, la mutation des risques et l'excès de confiance dans l'idée que la règle établie est la bonne[13].

La réglementation post-crise est spécifique à la crise : des risques sont identifiés, et des règles sont mises en place pour les pallier. Si tant est que toutes les faiblesses nous conduisant au marasme de la fin des années 2000 aient été repérées et traitées, une limite de cette démarche tient de à que les risques mutent (White, 2014). Ainsi, il n'est pas impossible que la réglementation définie par Bâle III soit inadaptée aux faiblesses du système bancaire des prochaines décennies. Pour reprendre l'exemple précédemment cité, les conséquences économiques et financières de la crise sanitaire de 2020 seront le terrain d'une évaluation, en pratique, de la pertinence du cadre réglementaire : si les répercutions de cette crise sur le secteur bancaire sont fondamentalement différentes de celles engendrées par l'euphorie puis la crise financière des années 2000, il y a fort à parier que la réglementation en vigueur ne sera pas en mesure d'assurer une résilience forte du système.

Nous soulignons ici la possibilité que Bâle III définisse un cadre prudentiel dont l'efficacité pourrait s'avérer éphémère. La réglementation nécessite soit de pouvoir s'adapter constamment, risquant ainsi que les ajustements se fassent *a posteriori* des crises[14], soit de proposer des règles dont l'efficacité est intertemporelle, c'est à dire, non spécifique aux risques identifiés d'une période.

Nous proposons dans cette thèse de répondre à cet enjeu, en n'évaluant pas l'atteinte des objectifs de chacune des règles, mais en nous intéressant à une dimension plus large de la réglementation : renforcer la stabilité financière (Chapitre 1) et diminuer le risque de faillite bancaire (Chapitre 2).

[13]Sans parler d'excès de dette publique, nous faisons ici référence au syndrome "cette fois c'est différent" (Reinhart et Rogoff, 2009) qui décrit la croyance générale dans l'idée que les crises appartiennent au passé.

[14]Cela a été le cas des trois accords de Bâle.

2.2 Répondre à la complexité par la complexité

Face à un système bancaire marqué par une complexité caractéristique à la fois des produits financiers et de la structure des banques qui le composent, les instances régulatrices répondent par... la complexité (Bignon *et al.*, 2018). Nous pouvons définir cette complexité réglementaire à deux niveaux.

Premièrement, nous avons à faire à un corpus de règles très fourni : les accords de Bâle III sont complexes par le nombre d'exigences réglementaires qu'ils définissent[15]. Le coût d'entrée pour comprendre le fonctionnement de la réglementation définie et recommandée par Bâle III est donc élevé. Ce niveau de complexité induit un manque de transparence dans le lien entre les règles et l'objectif de stabilité financière et dans l'appréhension des interactions potentielles entre les règles[16].

Par ailleurs, la réglementation est complexe en tant que telle, c'est à dire qu'elle établit des règles qui sont complexes dans leur définition. C'est le cas du ratio de liquidité de court-terme : le LCR. En effet, le calcul du dénominateur (les sorties nettes de liquidité dans une période de 30 jours de crise de liquidité) de ce ratio est difficilement reproductible à partir de données publiques, et la définition de son numérateur (les actifs liquides de haute qualité) est source de débats. C'est aussi le cas du ratio de solvabilité. En effet, la construction des actifs pondérés

[15] Il faut ajouter à cela, le fait que ces accords constituent des recommandations. Par conséquent, la complexité de la réglementation prudentielle actuelle tient aussi des différences dans la transposition de ces accords au sein des différentes juridictions : le RCAP (*Regulatoy Consistency Assessment Programme*) réalisé par la BIS, couvre 28 juridictions. Certaines d'entre elles, comme l'Europe, comptent plusieurs pays, dans lesquels les régulateurs nationaux gèrent localement la mise en place de certaines règles. Ainsi, à titre d'exemple, les règlements et directives européens CRR/CRD-IV, assurent la transposition des accords de Bâle III au niveau de l'Europe, offrant donc certaines différences avec la transposition de ces mêmes accords dans d'autres juridictions telles que la méthode de pondération des actifs par les risques, le calcul du score de systémicité des banques, etc. A un deuxième niveau, l'application du contrôle prudentiel en Europe revient en partie (pour ce qui concerne le Pilier 3 notamment) à la charge des régulateurs nationaux.

[16] La Banque d'Angleterre souligne aussi la complexité lexicale du corpus réglementaire (Amadxarif *et al.*, 2019).

par les risques est tout à la fois dépendante du cycle (Bignon *et al.*, 2018) et définie de manière assez floue pour que les banques les plus importantes puissent agir dessus pour réduire leur contrainte en capital (Carpenter et Moss, 2013). La compréhension des règles est complexe, leur calcul également et donc leur *reporting* aussi.

Ainsi, la complexité réglementaire génère un double problème d'opacité : le manque de visibilité globale des règles rend peu compréhensible l'information sur leur efficacité, un enjeu pourtant d'ordre public puisqu'elles doivent assurer la stabilité du système financier ; et une opacité qui rend nécessairement plus ardue la tâche du régulateur[17].

2.3 "Dommages collatéraux" potentiels

Nous avons abordé jusque-là l'efficacité de la réglementation en exposant son objectif de renforcement de la stabilité financière et comment les règles établies sous Bâle III sont supposées le remplir. Cependant, il ne faut pas que les exigences prudentielles se posent en contrainte au bon fonctionnement du secteur : les banques doivent pouvoir assurer leur rôle de création de liquidité et de transformation des risques. Nous abordons ici un argument souvent avancé par l'industrie bancaire, selon lequel la réglementation contraint les banques dans leur capacité à générer du profit, augmente leur coût de financement et détériore finalement leur rôle créditeur.

Un certain nombre d'études souligne le rôle de la rentabilité des banques dans la stabilité financière (Keeley, 1990; Xu *et al.*, 2019), et d'autres mettent en évidence une relation négative entre réglementation en capital trop forte et

[17] De ce point de vue, la complexité prudentielle favorise l'étroitesse des liens entre les instances de régulation publiques et l'industrie bancaire. Au delà du questionnement démocratique que cela pose, l'efficacité réglementaire s'en voit détériorée (Bignon *et al.*, 2018; Veltrop et Haan, 2014; Mishra et Reshef, 2018)

rentabilité (Goddard *et al.*, 2013; Baker, 2013). De ce point de vue, le renforcement des exigences bâloises de 2010 vient fragiliser le système bancaire et la stabilité financière.

Toutefois, ce point de vue est loin de faire consensus au sein de la littérature économique. En effet, plusieurs travaux montrent qu'une meilleure capitalisation des banques entraine une diminution du risque lié à leur activité et donc de leur coût de financement (Admati *et al.*, 2013; Gambacorta et Shin, 2018). Ainsi, plusieurs auteurs soutiennent qu'une relation positive peut être établie entre certaines règles prudentielles et la rentabilité bancaire (Berger, 1995; Berger et Bouwman, 2009; Iannotta *et al.*, 2007; Lee et Hsieh, 2013).

Le travail de recensement d'études réalisé par la BIS[18] souligne cette absence de consensus :

- Sur 25 études portant sur l'impact du ratio de capital sur l'activité de prêt des banques, 12 identifient un impact négatif, 13 un effet positif.
- Sur 18 études analysant l'effet du ratio de levier sur l'activité de prêt des banques, 5 obtiennent un impact négatif et 13 un impact positif.
- L'effet du LCR sur l'activité de prêt est estimé négatif 13 fois sur 18.
- 55 études portant sur les effets du ratio de capital sur les coûts de financement des banques sont recensées. 32 obtiennent un impact positif et 23 un impact négatif. La même répartition est obtenue concernant l'effet du ratio de levier.
- 34 papiers trouvent un effet positif du LCR sur le coût de financement et seulement 2 un impact négatif.
- La littérature est en revanche plus consensuelle quant à l'impact des ratios de capital, de levier et de liquidité sur le taux de prêt : l'effet est positif.

[18] Voir le projet *Financial Regulation Assessment: Meta Exercise* (FRAME) réalisé par la BIS.

Dans un contexte où le secteur bancaire est mis en concurrence avec des modes de financement alternatifs, non-intermédiés et souvent moins régulés[19], la fragilisation du secteur bancaire par la réglementation pourrait amoindrir ses effets sur la stabilité financière. Par conséquent, il nous semble pertinent de déterminer l'impact individuel et cumulé des différentes exigences réglementaires sur la rentabilité des banques, le niveau des crédits qu'elles accordent, ou encore le niveau des taux de ces crédits dans l'analyse de l'efficacité du règlement prudentiel.

3 Proposition d'une réponse

Cette thèse a pour objectif d'évaluer l'efficacité de la réglementation sous certains des différents angles évoqués précédemment. Plus précisément, nous évaluons l'efficacité de la réglementation sur les plans macroéconomique et microéconomique. Ce dernier est traité de deux points de vue différents : celui de l'objectif de renforcement de la solidité du secteur bancaire et celui des répercussions non désirées potentielles de la réglementation sur l'industrie bancaire.

L'une des ambitions de cette thèse, au delà de l'évaluation de l'efficacité de la réglementation prudentielle bancaire actuelle, est aussi de **proposer des réponses aux enjeux et limites de ces exigences réglementaires**. Plus précisément, nous proposons que la réglementation soit axée sur un ratio de levier plus mordant : cela permettrait à la fois de répondre à la nécessité d'une règle intertemporelle, moins complexe et non-contraignante pour le bon fonctionnement du secteur bancaire.

Le premier chapitre de cette thèse s'intéresse à l'efficacité de la réglementation prudentielle d'un point de vue macroéconomique et répond à la question : les

[19] Nous faisons ici référence au *shadow banking*.

exigences bâloises en capital et liquidité permettent-elles de renforcer la stabilité financière ? La réponse à cette interrogation se heurte dans un premier temps à la définition et la mesure de la stabilité financière. Le FMI propose une batterie d'indices de solidité financière[20]. De façon redondante, nous pouvons trouver parmi ces indicateurs, les montants de ratios prudentiels définis par Bâle III, agrégés aux niveaux national et régional : nous nous retrouvons donc à mesurer la stabilité financière par les ratios prudentiels, eux-mêmes construits sur l'hypothèse qu'ils renforcent la stabilité financière. Devant l'inexistence d'une mesure robuste et communément acceptée de stabilité financière, nous proposons dans un premier temps une méthode de calcul pour un tel indicateur fondé sur une analyse en composantes principales à partir de variables macroéconomiques. Dans un second temps, nous estimons l'impact individuel et combiné des ratios de capital et de liquidité sur cet indicateur. Pour ce faire, nous avons recours à l'estimation d'un modèle non-linéaire à transition lisse en panel (*Panel Smooth Transition Regression*, PSTR) sur des données comptables de 1600 banques agrégées au niveau de 23 pays et sur la période 2005-2016. Les estimations que nous menons différencient les banques en fonction de leur niveau de systémicité, nous permettant ainsi de prendre en compte l'un des aspects macruprudentiels de Bâle III. Nos résultats montrent que les ratios de capital et de liquidité ont un impact positif sur la stabilité financière pour de faibles valeurs. Lorsque ces ratios croissent, leur effet devient moins perceptible. Au delà des résultats de nos estimations, nous soutenons dans ce chapitre que pour pouvoir mener une politique macroprudentielle efficace et l'évaluer, il est nécessaire que le sujet de la mesure de la stabilité financière soit investi plus largement.

Dans le deuxième chapitre, nous abordons la question de l'efficacité réglementaire d'un point de vue microéconomique. L'objectif de ce chapitre est d'évaluer

[20]Voir *Financial Soundness Indicators* mis à disposition par le FMI.

l'effet des ratios de capital, de levier et de liquidité sur la probabilité de défaut des banques. La littérature aborde ce sujet de deux manières : *via* l'utilisation de mesures représentatives de la distance au défaut telles que le Z-score, et l'analyse d'observations de faillites bancaires. C'est la deuxième approche que nous adoptons. En effet, nous procédons à l'évaluation du pouvoir prédictif et de l'impact sur le défaut des banques d'un large panel de variables bilancielles bancaires. Pour cela, nous avons recours à trois modèles de classification : la régression logistique, les forêts aléatoires et les réseaux de neurones. Nous menons cette analyse sur un échantillon de 4707 banques américaines dont 454 défauts, et 3529 banques européennes dont 205 défauts, sur la période 2000-2018. Dans le cas des banques américaines, nos résultats soulignent une relation négative entre les ratios de capital et de levier sur la probabilité de défaut. L'effet de la liquidité ressort positif, ce que nous expliquons par la période de bas taux d'intérêt dans laquelle notre étude s'insère. Les résultats concernant les banques européennes sont plus délicats à interpréter, ce qui est dû à l'absence d'une liste publique et officielle des banques européennes ayant fait défaut. Dans l'ensemble, nos résultats nous conduisent à soutenir la mise en place d'un ratio de levier plus fort, au détriment d'un ratio de solvabilité moins important. En effet, ces deux ratios apparaissent aussi déterminants l'un que l'autre dans la probabilité de défaut. En revanche, le caractère intemporel et simple du ratio de levier lui donne un avantage certain pour répondre aux enjeux mis en évidence plus avant. Ces résultats sont corroborés par notre dernier chapitre.

Le troisième chapitre porte une analyse des déterminants de la rentabilité bancaire. Nous cherchons ici à évaluer l'efficacité de la réglementation prudentielle sur un plan microéconomique, au regard de ses répercussions éventuelles sur le bon fonctionnement de l'industrie bancaire. Nous cherchons également à évaluer l'effet combiné des ratios prudentiels sur la rentabilité bancaire. De la même manière que pour le chapitre précédent, nous avons recours à un large échantillon de variables bilancielles. Nous scindons notre bases de données en deux : l'une contient le LCR et couvre la période 2012-2018 pour un peu plus de 300 banques, et l'autre sans le LCR[21] de 2000 à 2018 pour plus de 1100 banques. Afin de renforcer la qualité de nos résultats, nous faisons également appel à plusieurs mesures de rentabilité. En outre, nous comparons les effets des ratios prudentiels sur la rentabilité mesurée par le rendement des actifs moyens (*Return On Average Assets*, ROAA) et par le rendement des capitaux propres moyens (*Return On Average Equity*, ROAE). Deux modèles sont utilisés pour mener nos estimations : le modèle Lasso et les forêts aléatoires. Nos résultats montrent que le ratio de levier a un impact positif sur la rentabilité mesurée par le ROAA. En revanche, l'impact de ce même ratio sur la valeur actionnariale, mesurée par le ROAE, est généralement faible mais négatif. Néanmoins, nous obtenons que ce ratio prédomine les ratios de capital et de liquidité dans la détermination de la rentabilité[22]. Nous déduisons de ces résultats qu'un ratio de levier fort ne contraint pas les performances de l'activité bancaire mais celles de la valeur actionnariale. Si ces résultats peuvent expliquer la virulence de l'industrie bancaire à s'opposer à de fortes contraintes en levier, ils viennent certainement confirmer l'idée selon laquelle un ratio de levier pourrait constituer une piste d'amélioration de la réglementation pour qu'elle réponde aux enjeux explicités précédemment.

[21]Le LCR est mis en place récemment et encore peu de données sont disponibles.

[22]D'une part, nous obtenons que l'importance prédictive de ce ratio est supérieure à celle des deux autres. D'autre part, quand nous étudions l'impact cumulé du ratio de levier avec le ratio de capital ou de liquidité, il apparait que l'effet du ratio de levier outrepasse celui des deux autres.

4 Conclusion

L'occurrence d'une crise souligne les leçons qui n'ont pas été apprises de la dernière. "Cette fois, c'est différent", ou non, quoi qu'il en soit nous nous attelons à modifier les règles du jeu pour tenter de prévenir toute nouvelle dégénérescence du système. Bien souvent, une courbure de l'espace des risques s'opère et de nouvelles dérives ou perturbations apparaissent. C'est comme si Kitchin, Juglar et Kondratief détenaient la formule de l'univers. La crise de 2007-09 déroge-t-elle à la règle ? Elle nous a très certainement montré les faiblesses du système bancaire et financier dans lequel nous évoluions et d'importants remaniements prudentiels ont été menés en conséquence. Cette refonte des règles prudentielles suffira-t-elle à assurer la stabilité financière ? Le nouveau contexte réglementaire permettra-t-il de prévenir, ou tout du moins amoindrir les effets de la prochaine "purge" du système ? Les accords de Bâle III ont-ils résolu le "paradoxe de la tranquillité" ? Autant de questions auxquelles la crise sanitaire liée au Covid 19 risque malheureusement de répondre. Autant de questions auxquelles cette thèse ne répond pas. Ou presque. En effet, **nous menons dans cette thèse une analyse de l'efficacité réglementaire à plusieurs niveaux : au plan macroéconomique d'une part, et au plan microéconomique d'autre part. Nous abordons cette problématique en évaluant à la fois l'efficacité règlementaire du point de vue de ses objectifs et des dommages collatéraux éventuels qu'elle peut produire.** A ce titre, nous apportons un certain nombre de réponses aux enjeux identifiés en introduction.

Le premier chapitre s'intéresse à l'efficacité règlementaire sur un plan macroéconomique, évaluant ainsi l'un des aspects novateur et central de la règlementation de Bâle III : la règlementation macroprudentielle. Nos résultats mettent en évidence l'existence de non-linéarités dans l'impact des ratios de capital et de liquidité sur la stabilité financière. Ce chapitre apporte également une contribution à la littérature existante dans la mesure où il souligne l'importance pour les régulateurs de se doter des outils nécessaires à l'évaluation de l'efficacité des politiques prudentielles. En outre, la constitution d'un indicateur de stabilité financière nous parait primordial.

Dans le deuxième chapitre, nous évaluons l'effet des ratios de capital, de levier et de liquidité sur la probabilité de défaut des banques. Nos résultats sur l'échantillon des banques américaines montrent très nettement que, au delà de la rentabilité mesurée par le rendement des actifs moyens, les ratios de capital et de levier sont prédominants dans la prédiction du défaut. Nous obtenons pour ces deux ratios, un impact négatif, ce qui est en accord avec l'intuition et la théorie économique. Nous confirmons l'idée selon laquelle l'accumulation de ratios n'est pas nécessaire : une règlementation basée sur un ratio de levier plus mordant serait au moins aussi efficace, quitte à ce que le ratio de solvabilité, très complexe, soit amoindri. Nous soutenons qu'une telle orientation de la politique prudentielle permettrait tout à la fois d'assurer une baisse de la probabilité de défaut des banques, diminuer la complexité du corpus règlementaire et pallier les risques du secteur bancaire de façon moins spécifique et donc plus intemporelle.

Pour pouvoir acter la pertinence de notre proposition (axer la règlementation sur un ratio de levier plus élevé), et évaluer l'efficacité de la règlementation sous l'angle de ses dommages collatéraux potentiels sur l'industrie bancaire, nous procédons dans le troisième chapitre à l'estimation des impacts des ratios de capital, de levier et de liquidité sur la rentabilité des banques. Nos résultats montrent que le ratio de levier est le ratio prudentiel prenant le plus d'importance dans la détermination de la rentabilité lorsque celle-ci est mesurée par le rendement des actifs. Par ailleurs, nous obtenons une relation positive entre le levier et la rentabilité. Ces résultats viennent confirmer le fait qu'une règlementation plus forte en levier ne constitue pas une contrainte pour l'activité des banques. Une contrainte apparait néanmoins sur la rentabilité actionnariale. En effet, un impact négatif du levier émerge lorsque l'on s'intéresse à la rentabilité telle que mesurée par le rendement des capitaux propres. Nous en déduisons que la ferveur avec laquelle l'industrie bancaire s'oppose à la mise en place d'un ratio de levier fort, n'est pas basée sur l'idée qu'une telle règlementation, en détériorant la rentabilité de l'activité des banques, porterait un coût social, mais un coût privé supporté par l'actionnariat bancaire.

Ainsi, une contrainte en levier plus mordante que l'exigence actuelle de 3% diminuerait la probabilité de défaut des banques et aurait un impact positif sur la rentabilité bancaire mesurée par le rendement des actifs. En outre, favoriser le levier permettrait de clarifier une règlementation devenue trop complexe, et d'en faciliter l'évaluation de l'efficacité. Enfin, une contrainte plus forte en levier offre à la fois l'avantage de laisser moins de liberté d'optimisation interne et d'être plus intemporelle.