Essays on post-crisis banking supervision

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THÈSE
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Essais sur la supervision bancaire d'après crise

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Résumé

Dans un contexte économique et réglementaire marqué par les suites de la crise financière de 2007-2008, cette thèse a pour objectif de contribuer empiriquement à la littérature académique de l'économie bancaire en abordant successivement trois thématiques reliées au thème commun de la crise bancaire.

La première thématique est celle de l'émergence d'une défaillance bancaire individuelle qui, lorsqu'elle concerne un établissement de grande envergure, ou simultanément plusieurs établissements plus modestes, peut déboucher sur une crise bancaire. En analysant 449 banques françaises entre 1997 et 2013, le chapitre 1 montre l'intérêt d'appliquer un modèle de détection avancée des défaillances bancaires dans le cas du système bancaire français. Les résultats valident la pertinence d'utiliser le groupe de variables classiquement employées dans la littérature et soulignent l'importance de prendre en considération la typologie des banques en fonction de leur actionnariat.

La deuxième thématique est celle du risque systémique que font peser les entités "trop grandes pour faire faillite" (*too-big-to-fail*), et dont les difficultés peuvent faire survenir une crise bancaire, comme ce fut le cas en 2008. Le chapitre 2 évalue l'impact de la réglementation destinée à traiter ce problème émanant des établissements bancaires d'importance systémique mondiale (G-SIBs - *global systemically important banks*) en utilisant un panel international de 97 grandes banques, entre 2005 et 2016, réparties dans 22 pays. Il s'avère que suite à cette réglementation, ces entités ont substantiellement réduit l'expansion de leurs bilans. Aucune conséquence négative quant au financement de l'économie n'est observée. Toutefois, la permanence d'un avantage des G-SIBs pour leur coût de financement suggère que certaines distorsions liées au problème du *too-big-to-fail* tendent à persister.

La troisième thématique est celle de la distribution du crédit bancaire aux entreprises en période de crise. Que le choc initial provienne de la sphère financière comme en 2008-2009, ou bien constitue un simple retournement de tendance conjoncturel, le chapitre 3 s'intéresse à la dynamique de l'octroi de crédit aux entreprises en France au cours du cycle économique, et plus particulièrement aux asymétries entre types de banque. Les résultats, basés sur un panel de 276 banques et 13 125 entreprises entre 1999 et 2019, montrent que les banques privées tendent à allouer leur crédit de manière procyclique tandis que les banques publiques présentent un comportement plutôt acyclique. Entre les deux, les banques mutualistes paraissent moins procycliques que les banques privées.

Summary

In an economic and regulatory context shaped by the aftermath of the 2007-2008 financial crisis, the purpose of this thesis is to contribute to the empirical academic literature of the field of banking economics by addressing three topics related to the common theme of the banking crisis.

As first topic, this thesis deals with the emergence of an individual bank failure, which can lead to a banking crisis when it concerns a large bank or several smaller institutions simultaneously. Focusing on 449 French banks between 1997 and 2013, chapter 1 shows the interest of applying an early warning system to anticipate bank failures in the case of the French banking system. The results validate the relevance of using the usual set of variables commonly seen in the literature. They also underline the necessity to take into account the type of bank, depending on their ownership, to improve the efficiency of the model.

The second topic is the systemic risk posed by "too big-to-fail" banks whose difficulties can lead to a banking crisis, as it was the case in 2008. Chapter 2 assesses the impact of the regulation designed to address this issue of global systemically important banks (G-SIBs) using an international panel of 97 large banks, between 2005 and 2016, located in 22 different countries. It turns out that following this regulation, these entities have substantially curbed the expansion of their balance sheets. We observed no negative consequences for the financing of the economy. However, as the G-SIBs' funding cost advantage remains, it suggests that some distortions linked to the too-big-to-fail problem tend to persist.

The third chapter addresses the topic of the distribution of credit to non-financial corporates in times of crisis. Whether the initial shock comes from the financial sphere, as in 2008-2009, or constitutes a simple reversal of the economic trend, chapter 3 examines the dynamics of credit to corporates in France over the economic cycle, and more particularly focuses on the asymmetries between types of bank. Based on a panel of 276 banks and 13,125 firms between 1999 and 2019, the results show that private banks tend to allocate credit in a procyclical manner while state-owned banks exhibit a rather acyclical behavior. Between them, cooperative banks appear less procyclical than private banks.

Mots-clés

Défaillance bancaire, modèle de détection avancée, CAMELS, système bancaire français

Banques systémiques, trop grandes pour faire faillite, levier financier, rentabilité, distorsions

Banques mutualistes, banques publiques, procyclicité, octroi de crédit, relations banque-entreprise

Keywords

Bank distress, Early Warning System (EWS), CAMELS, French banking system

Systemic banks, too-big-to-fail, leverage, profitability, distortions

Cooperative banks, state-owned banks, procyclicality, credit supply, bank-firm relations

Avertissements

Les différents chapitres de cette thèse sont des articles de recherche rédigés en anglais ayant chacun une structure autonome. Ceci explique la présence des termes "paper" et "article" ainsi que la possible répétition de certaines informations.

L'introduction générale est quant à elle rédigée en français. Elle décrit quelques caractéristiques essentielles du système bancaire français d'où découlent les thématiques principales de cette thèse. Elle présente ensuite succinctement le contenu de chacun des trois chapitres de la thèse.

La présentation du chapitre 2 correspond à celle de la version publiée par l'International Journal of Central Banking en octobre 2020.

Les idées et opinions exposées dans ces articles sont les miennes, et celles de mes co-auteures, et ne reflètent pas nécessairement celles de l'Autorité de contrôle prudentiel et de résolution (ACPR), de la Banque de France et de l'Eurosystème.

Disclaimers

Although they are related, the following chapters of this thesis are independent research articles. Consequently, the words "paper" and "article" are used extensively, and some information can appear in several places.

The general introduction is written in French. It describes some key characteristics of the French banking sysem which lead to the main topics of this thesis. Then it briefly presents the content of each of the three chapters of the thesis.

The layout of chapter 2 corresponds to the version published by the International Journal of Central Banking in October 2020.

The views and opinions expressed in these articles are mine, and those of my co-authors, and do not necessarily reflect the official policy or position of the Autorité de contrôle prudentiel et de résolution (ACPR), the Banque de France, or the Eurosystem.

À Alcyone et Laura,

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Sommaire

Introduction générale

Cette thèse aborde plusieurs thématiques de supervision bancaire, dans un contexte économique et réglementaire marqué par la crise financière de 2008-2009, en ayant pour prisme les spécificités du secteur bancaire français.

Avec plus de 8 600 milliards d'euros d'actifs à leurs bilans fin 2019, soit environ 3,5 fois le produit intérieur brut (PIB) du pays, les banques françaises occupent une place prépondérante en Europe. Depuis l'entrée en vigueur du Mécanisme de surveillance unique (MSU) en novembre 2014 qui a conduit les principales banques des pays membres de la zone euro à être placées sous la supervision directe de la Banque centrale européenne (BCE), les banques françaises concernées représentent environ un tiers des actifs agrégés du MSU (cf. ACPR [2020b]). Au niveau mondial, le système bancaire français se distingue également par son fort degré d'internationalisation - environ 37% des prêts octroyés par les banques françaises le sont à l'étranger (op. cit.) - et par la présence d'établissements de grande taille se hissant parmi les plus importantes au monde en termes d'actifs inscrits à leurs bilans.

L'importance du secteur bancaire français pour le financement de l'économie nationale, mais également son poids notable à l'échelle européenne et internationale, rendent primordiale l'étude de ses caractéristiques et justifient une analyse approfondie des problématiques qui en découlent. Le secteur bancaire français présente quatre caractéristiques essentielles détaillées ci-dessous et qu'il convient de bien expliciter car celles-ci sous-tendent les thématiques abordées dans cette thèse. Même si à elles quatre elles ne peuvent ni résumer l'ensemble des particularités de ce secteur d'activité complexe, ni ne s'avèrent exclusivement spécifiques au système bancaire français, elles n'en demeurent pas moins structurantes pour celui-ci.

Caractéristiques du système bancaire français

Caractéristique n°1 : Une intermédiation bancaire encore marquée

Le secteur privé (ménages et entreprises) de l'économie française dépend très fortement du système bancaire pour assurer son financement. Pour les ménages, principalement en recherche de crédits immobiliers et de crédits de trésorerie, les banques sont quasiment incontournables, mais il en est presque de même pour les entreprises. En effet, en 2020, les sociétés non financières en France se financent encore aux deux tiers auprès des banques, et seulement le tiers restant provient du financement de marché (émissions de titres de dette) - cf. Banque de France [2021] et graphique ci-dessous. Même si cette proportion montre une légère baisse au cours des 12 dernières années, elle demeure élevée et relativement plus haute que dans d'autres pays, notamment aux États-Unis (cf. Artus [2013]). Un tel degré d'intermédiation bancaire dans le financement du secteur privé impose donc de s'assurer de la robustesse collective du système bancaire et de celle de chacune de ses entités, nécessitant l'exercice d'une supervision bancaire rapprochée.

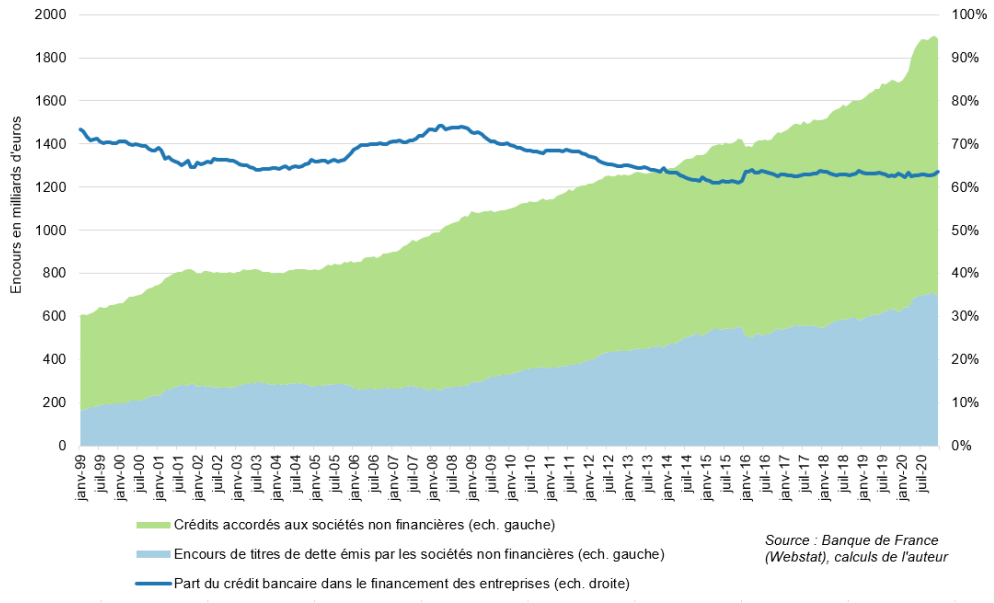

Figure 1: Part du crédit bancaire dans le financement des entreprises en France entre 1999 et 2020

Caractéristique n°2 : Un nombre très réduit de faillites bancaires

Contrairement à d'autres systèmes bancaires, celui de la France se caractérise par une quasi absence de faillites bancaires, à l'inverse notamment des États-Unis où de nombreuses banques disparaissent régulièrement et où même des établissements de grande taille comme Lehman Brothers peuvent être conduits à déposer le bilan. Depuis le cas complexe du Crédit Lyonnais en 1993, le système bancaire français n'a plus été confronté à de faillites notables. Ce nombre très réduit de faillites bancaires dans l'histoire récente du secteur peut certes traduire une résilience des établissements, mais ils ne sont pas pour autant exempts de vulnérabilités. Cela se révèle en réalité également lié à un interventionnisme des pouvoirs publics. Au plus fort de la crise financière de 2008, la création de la Société de financement de l'économie française (SFEF), autorisée par la Commission européenne (cf. Commission européenne [2008]), a permis d'apporter un soutien aux banques françaises pour leur refinancement (donc leur liquidité), mais leur solvabilité n'était pas menacée. Au-delà de cet exemple, l'intervention des pouvoirs publics se trouve principalement dans la conduite d'une supervision par la Commission bancaire, puis par l'Autorité de contrôle prudentiel et de résolution (ACPR), cherchant à anticiper les difficultés des banques et à les résoudre ex-ante, plutôt que de traiter des faillites ex-post.

Caractéristique n°3 : La présence de banques systémiques

Observé au niveau des groupes bancaires (au plus haut niveau de consolidation comptable), le secteur bancaire français s'avère relativement concentré : les six principaux groupes totalisent environ 80% des actifs de l'ensemble du secteur (ACPR [2020b]). Il en résulte que les grands groupes bancaires français présentent une taille conséquente à l'échelle nationale et/ou internationale. Sept d'entre eux sont donc considérés comme systémiques au niveau domestique et figurent sur la liste des "autres établissements d'importance systémique" - A-EIS - (cf. ACPR [2020a]), et quatre sont même désignés

comme établissements d'importance systémique mondiale - EISm - par le Conseil de stabilité financière (*Financial Stability Board - FSB)* - cf. FSB [2020]. Mise à jour chaque année, cette liste internationale ne compte généralement que trente banques, dont huit pour la zone euro. Avec quatre banques systémiques au niveau mondial, la France est donc particulièrement concernée par la problématique du *"too-big-to-fail"* associée à ces entités systémiques.

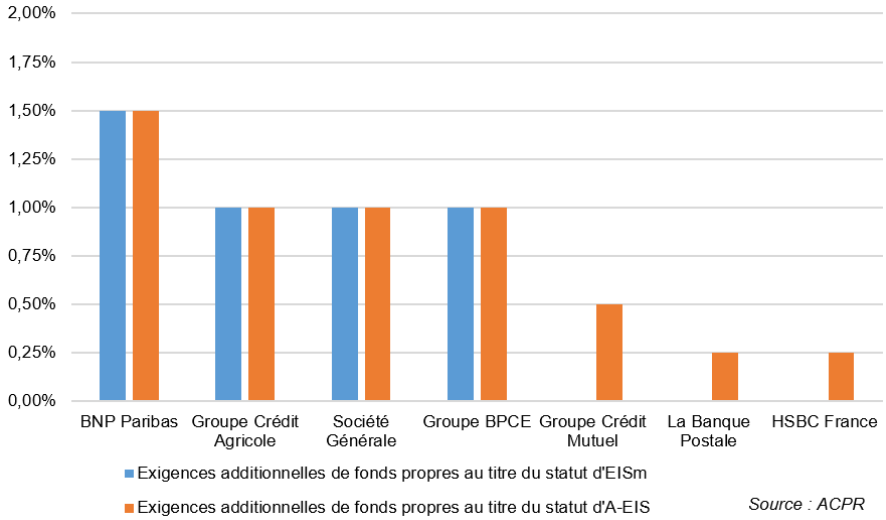

Figure 2: Groupes bancaires désignés comme systémiques au niveau national (A-EIS) et/ou mondial (EISm) au 31/12/2019 en France et exigences additionnelles de fonds propres associées à ces statuts

Caractéristique n°4 : La présence de banques mutualistes

Le secteur bancaire français présente une variété d'acteurs différant par leur structure actionnariale. Si de nombreuses banques en France sont des sociétés de droit privé dont le capital est contrôlé par des actionnaires privés (certaines d'entre elles étant cotées en bourse), d'autres moins nombreuses sont à actionnariat public. Mais surtout, la France est caractérisée par l'existence de groupes bancaires dits "mutualistes". Officiellement identifiés par le Code monétaire et financier (article L511-30), trois groupes mutualistes (les groupes Crédit Agricole, Crédit Mutuel et Banques Populaires Caisses d'Épargne -

BPCE) sont organisés en réseaux de banques régionales autour d'un organe central. Leur actionnariat diffère des investisseurs privés traditionnels en ce sens que les propriétaires de ces banques en sont également nécessairement des clients (dénommés "sociétaires") et que la gouvernance de ces entités repose sur le principe "un homme, une voix". Par ailleurs ces entités ne sont pas cotées. Cette variabilité actionnariale est donc à prendre en compte dans la mesure où elle peut influer sur les thématiques analysées.

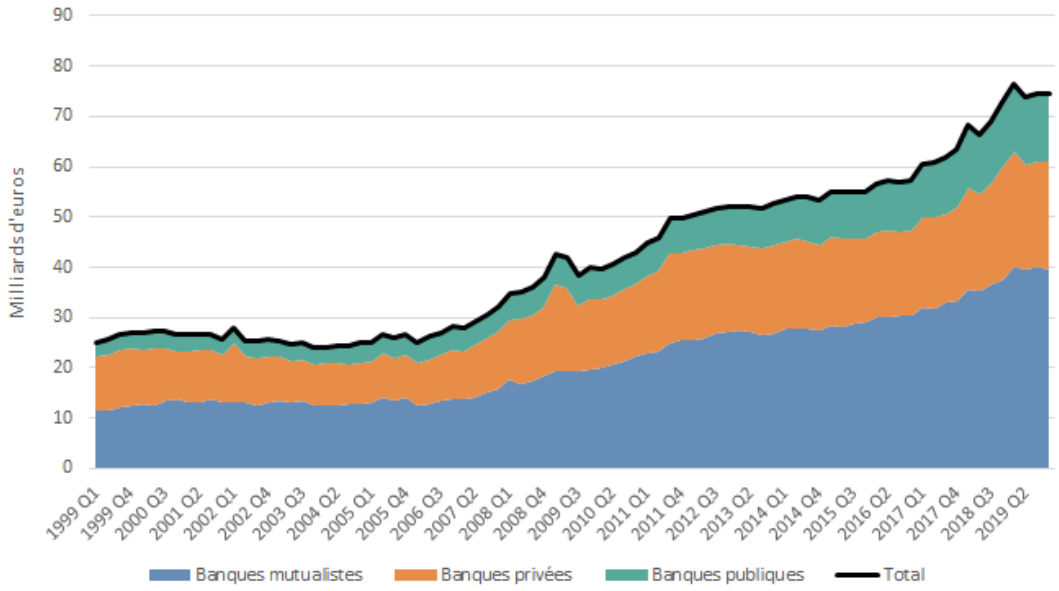

Figure 3: Répartition par type de banque du crédit au panel d'entreprises "multi-bancarisées" utilisé dans le chapitre 3

Composition et organisation de la thèse

En ayant à l'esprit ces particularités du système bancaire français, cette thèse porte sur diverses problématiques reliées à la supervision bancaire dans un contexte d'après crise. Dans un environnement économique et réglementaire postérieur à la crise financière

de 2007-2008, cette thèse a pour objectif de contribuer empiriquement à la littérature académique de l'économie bancaire en abordant successivement trois thématiques. Chacune de ces trois thématiques est spécifiquement développée dans un chapitre dédié de cette thèse. Chaque chapitre constitue donc un article autonome, mais ils sont néanmoins reliés par le thème central de la *crise bancaire* et leurs problématiques découlent directement des caractéristiques du secteur bancaire français exposées précédemment. Le schéma ci-dessous illustre les liens entre ces caractéristiques et les trois chapitres de cette thèse.

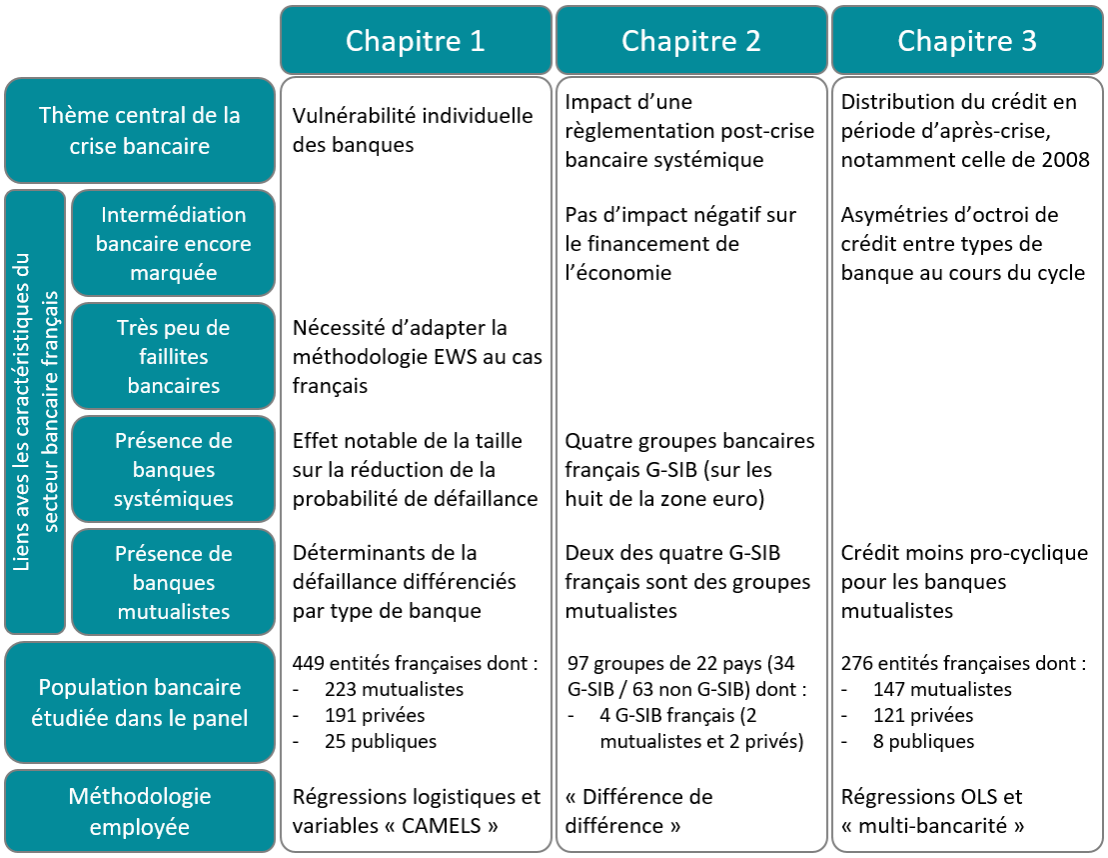

Figure 4: Liens entre les caractéristiques du système bancaire français et les trois chapitres de cette thèse

La première thématique est celle de l'émergence d'une **défaillance bancaire** individuelle qui, lorsqu'elle concerne un établissement de grande envergure, ou simultanément plusieurs établissements plus modestes, peut déboucher sur une crise bancaire. Le chapitre 1 a pour but d'investiguer la pertinence d'un modèle de détection avancée des défaillances bancaires (*early warning system*) dans le cas du système bancaire français. Les faillites bancaires étant très rares en France (cf. caractéristique n°2), l'application de ce type de modèle nécessite donc un élargissement du concept de défaillance. Nous utilisons donc une nouvelle source de données fondée sur la notation interne du superviseur bancaire français pour identifier les banques en défaillance. Nous appliquons ensuite la méthodologie traditionnelle reposant sur des régressions logistiques et un ensemble de variables explicatives dites "CAMELS", couramment employées dans la littérature, que nous complétons d'autres variables, notamment de liquidité interbancaire. Nos résultats valident dans l'ensemble la pertinence du groupe de variables "CAMELS" pour le système bancaire français, tout en soulignant d'une part le rôle clé des variables de rentabilité dans la prévision ex-ante des défaillances bancaires individuelles, et d'autre part la dimension discrétionnaire demeurant dans l'appréciation du superviseur. Par ailleurs, la prise en compte de la diversité des structures actionnariales des banques (cf. caractéristique n°4) révèle que les déterminants principaux de la défaillance varient entre banques privées et mutualistes.

La deuxième thématique est celle du **risque systémique** que font peser sur le système financier les entités "trop grosses pour faire faillite" (*too-big-to-fail*), et dont les difficultés peuvent faire survenir une crise bancaire, comme ce fut le cas en 2008. Comme exposé ci-dessus, la France est particulièrement concernée par ce sujet (cf. caractéristique n°3). Le chapitre 2, co-écrit avec Dominique Durant et Oana Toader, propose une évaluation de l'impact de la réglementation mise en œuvre par le Comité de Bâle suite à la faillite de Lehman Brothers pour traiter ce problème émanant des

établissements bancaires d'importance systémique mondiale (G-SIBs - *global systemically important banks*). Notre approche économétrique permet de quantifier les impacts que la désignation de ces entités en tant que G-SIB a eu sur leur activité. Nous montrons que, suite à cette désignation, les G-SIBs ont substantiellement réduit l'expansion de leurs bilans, ce qui leur a permis de combler leur retard en termes de ratio de levier financier, dans un contexte de croissance générale des fonds propres prudentiels. Nous ne constatons aucune conséquence négative quant au financement de l'économie, sujet crucial pour le cas français compte tenu de la prépondérance des banques - et notamment celles qui sont systémiques - dans le financement de l'économie (cf. caractéristique n°1). Toutefois, la permanence d'un avantage des G-SIBs pour leur coût de financement suggère que certaines distorsions liées au problème du *too-big-to-fail* tendent à persister. L'article composant ce chapitre 2 a fait l'objet d'une publication dans l'*International Journal of Central Banking* en octobre 2020.

La troisième thématique quant à elle est celle de la **distribution du crédit bancaire aux entreprises en période de crise**, sujet d'autant plus critique compte tenu de la caractéristique n°1 mentionnée plus haut. Que le choc initial provienne de la sphère financière comme en 2008-2009, ou bien constitue un simple retournement de tendance conjoncturel, le chapitre 3 s'intéresse à la dynamique de l'octroi de crédit aux entreprises en France au cours du cycle économique, et plus particulièrement aux asymétries entre types de banque. Ce faisant, l'article explore donc pleinement l'un des aspects de la caractéristique n°4 du système bancaire français (cf. supra). Nous utilisons une base de données très granulaire sur les encours de crédit au niveau banque-entreprise et appliquons une stratégie d'identification fondée sur la "multi-bancarité" pour contrôler les effets de demande. Nous montrons que les banques privées tendent à allouer leur crédit de manière pro-cyclique tandis que les banques publiques présentent un comportement plutôt acyclique. Entre les deux, les banques mutualistes paraissent moins pro-cycliques

que les banques privées. Nous montrons également que suite aux plus sévères perturbations macroéconomiques au lendemain de la grande crise financière de 2008, les banques mutualistes ont beaucoup moins réduit leur offre de crédit que les banques privées, tandis que les banques publiques n'ont pas réagi de manière significative à ce choc extrême.

Dans les sections suivantes, nous introduisons tout d'abord successivement chacune de ces trois thématiques, ce qui permet dans un second temps d'apprécier l'insertion de chacun des trois chapitres de cette thèse dans leurs littératures respectives et d'en souligner les principales contributions.

Les modèles *early warning system* et les variables *CAMELS*

Les faillites bancaires peuvent avoir des effets catastrophiques à la fois pour le secteur financier et pour l'ensemble de l'économie, en particulier dans le cas des banques systémiques, comme l'ont rappelé la faillite des Lehman Brothers et les conséquences macroéconomiques à long terme induites par la grande crise financière de 2008. Par conséquent, être en mesure de prédire la défaillance des banques, ou du moins de mieux identifier ex-ante les facteurs de vulnérabilité de celles-ci s'avère crucial, tant dans la perspective microprudentielle du superviseur que du point de vue macroéconomique. C'est le but d'une classe de modèles dits de détection avancée des défaillances bancaires (en anglais *early warning systems*), ci-après désignés "EWS". À partir de la fin des années 1970, un courant de littérature s'est mis à appliquer des techniques de régression logistique destinées à identifier les déterminants ex-ante des défaillances des banques (voir notamment Martin [1977], Hanweck [1977], Hanweck and Avery [1984], Barth et al. [1985] ou encore Pantalone and Platt [1987]).

Suite à la crise financière mondiale de 2008 qui a vu de nombreuses banques faire faillite ou être secourues par des interventions étatiques dans le monde entier, l'intérêt pour ce courant de la littérature s'en est trouvé renouvelé. De nouveaux articles relatifs à la supervision bancaire et à la faillite des banques sont parus ces dernières années (voir notamment Cole and White [2011], DeYoung and Torna [2013], Fungàcovà and Weill [2013], Calice [2014], Mayes and Stremmel [2014] et Betz et al. [2014]). La majorité des articles de cette littérature reposent sur des modèles économétriques basés sur des régressions logistiques multivariées dont l'objectif est de déterminer quelles métriques à l'instant t sont des déterminants pertinents des défaillances des banques à $t+1$.

L'ensemble des variables explicatives couramment employées comme déterminants ex-ante de la défaillance est regroupé sous l'acronyme "CAMELS", très bien décrit notamment par Mayes and Stremmel [2014]. Chacune de ces six lettres désigne une catégorie de variables liées à une thématique : l'adéquation du niveau des fonds propres (*Capital adequacy*), la qualité des actifs détenus par la banque (*Asset quality*), la rigueur du management de l'entreprise (*Management*), la capacité de la banque à générer du bénéfice (*Earning ability*), la situation de liquidité de l'établissement (*Liquidity*) et sa sensibilité au risque de marché (*Sensitivity to market risk*). Pour chacune de ces six catégories, le tableau ci-dessous donne quelques exemples de variables que l'on rencontre couramment dans cette littérature et leur impact théorique attendu sur la probabilité de défaillance de l'établissement.

La majorité des articles de cette littérature portent soit sur des banques américaines, à l'image de Cole and White [2011] ou DeYoung and Torna [2013] qui appliquent ce type de modèle sur un panel de banques aux États-Unis, soit sur des panels internationaux (voir Betz et al. [2014] ou Calice [2014]). Des variations intéressantes apparaissent d'un article à l'autre en ce qui concerne la variable dépendante des modèles économétriques :

CAMELS	Variables (exemple)	Impact théorique attendu sur la vulnérabilité d'une banque
C	- Ratio de solvabilité (pondéré) - Ratio de levier (non pondéré)	Les banques les mieux capitalisées sont en théorie mieux armées pour résister aux chocs de par la capacité d'absorption des pertes de leurs fonds propres.
A	- Ratio de prêts non performants - Provisionnement des pertes	Des actifs de meilleure qualité doivent générer moins de risque et moins de perte, donc réduire la probabilité de défaillance.
M	- Ratio de coûts sur revenus	La rigueur du management de la banque est vue comme un proxy de sa qualité et de sa capacité à prémunir la banque contre les chocs.
E	- Marge nette d'intérêt - ROA (rendement des actifs) - ROE (rendement des capitaux propres)	La capacité d'une banque à générer des revenus lui permet de partir d'une situation plus favorable pour absorber d'éventuelles pertes ou reconstituer du capital. Mais des rendements plus haut peuvent aussi être le signe d'un risque plus élevé et donc d'une plus grande vulnérabilité.
L	- Part des actifs liquides (*HQLA*) - Ratio crédits sur dépôts - Ratios LCR ou NSFR	Une banque disposant d'actifs liquides peut plus aisément les céder en cas de besoin rapide de trésorerie.
S	- Part des revenus du trading	Une banque plus exposée au risque de marché introduit un risque supplémentaire par rapport à son principal risque (le risque de crédit), pouvant donc la rendre plus vulnérable.

Figure 5: Exemples et justifications des variables CAMELS

celle qui permet de caractériser la défaillance bancaire. Si certains articles comme Mayes and Stremmel [2014] et Betz et al. [2014] la définissent comme une réelle faillite juridique de la banque ou un sauvetage de la part d'une entité publique, d'autres recourent à des définitions plus larges, comme Miller et al. [2015] qui implique des notations d'agences, ou encore recourent à des données de marché pour calculer une "distance au défaut" (voir Blundell-Wignall and Roulet [2013] ou Zhichao et al. [2014]). La définition de cette variable s'avère donc cruciale, et il convient de bien l'adapter à la situation du système bancaire étudié.

Un modèle de détection avancée des défaillances bancaires en France fondé sur la notation du superviseur et des ratios financiers (chapitre 1)

L'objectif et la contribution principale du premier chapitre de la thèse est donc d'appliquer cette classe de modèle au cas du système bancaire français. La faillite d'une banque étant un événement extrêmement rare en France - fort heureusement pour les déposants et les superviseurs - cette situation assez différente de celle des États-Unis conduit donc à adapter la problématique au cas français. En effet, pour construire un modèle économétrique dont l'objectif est de prévoir la "défaillance" bancaire, il faut d'abord retenir une définition qui ne se limite pas à la pure faillite.

Dans ce chapitre 1, nous nous appuyons sur une source d'information innovante. L'autorité de supervision prudentielle française a utilisé une méthodologie de notation entre 1997 et 2013 pour évaluer la situation des banques. En utilisant cette méthodologie commune et toutes les sources disponibles d'informations quantitatives et qualitatives dont ils disposent sur les banques (notamment le reporting prudentiel quantitatif, certains documents internes des banques, entretiens périodiques avec la direction générale de la banque, les rapports d'inspections sur place, etc.), les superviseurs évaluent la situation des banques au moins une fois par an. L'un des résultats de cette évaluation est un score global compris entre 1 (situation très saine) et 5 (situation très dégradée). Utiliser cette notation du superviseur pour définir les banques en difficulté présente pour avantage de nous permettre d'élargir la définition de la "défaillance", et de nous donner des informations privilégiées sur la santé des banques. Cette donnée est donc particulièrement bien adaptée à un tel modèle EWS. Par conséquent, le but de ce papier est d'identifier les principaux facteurs de vulnérabilité des banques (tel qu'évaluée par le superviseur), et non pas de prédire les faillites réelles au sens juridique du terme.

Nous définissons donc les banques comme "défaillantes" lorsque leur notation se trouve dégradée au cours de l'année d'une note de 1, 2 ou 3 vers la note de 4 ou 5. On identifie ainsi 224 situations de défaillance sur un total de plus de 5 000 observations. Le panel est composé de 449 banques distinctes sur une période de 17 ans (1997-2013) avec des données à fréquence annuelle.

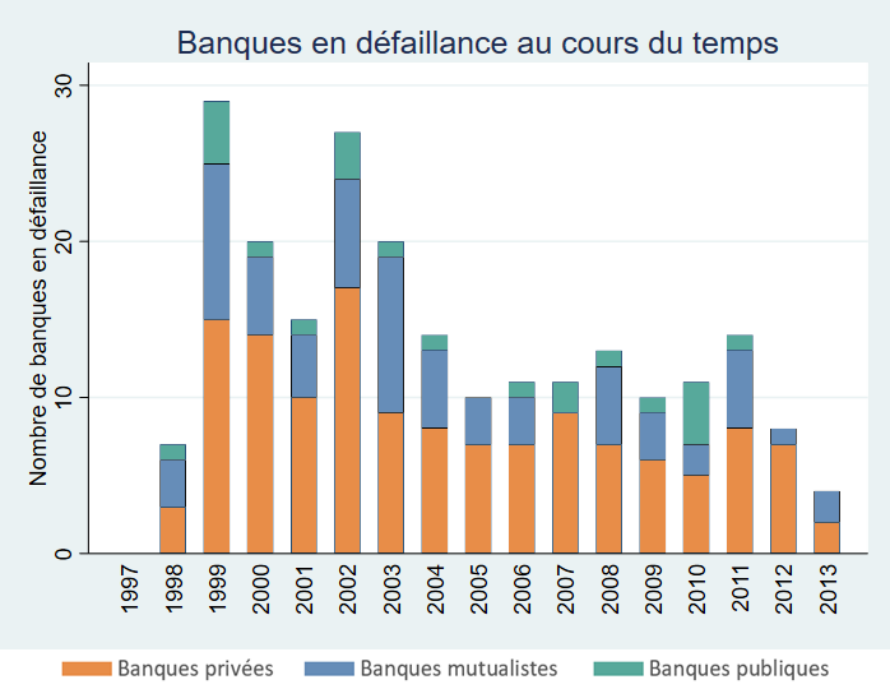

Figure 6: Nombre de situations de défaillance par année et type de banque

Pour l'ensemble des banques du panel, nous collectons les variables explicatives *"CAMELS"* suivantes :

- C : le ratio de solvabilité et le ratio de levier ;
- A : la part des prêts non performants et le ratio de provisionnement ;
- M : le coefficient d'exploitation et la part des dépenses de personnel ;
- E : le ratio du produit net bancaire normé par le total d'actifs, ainsi que le rende-

ment des actifs (ROA) et sa volatilité ;

- L : le ratio crédits sur dépôts et un proxy du ratio bâlois NSFR ;
- S : la part du risque de marché dans le total des actifs pondérés (RWA) et la part des actifs détenus à des fins de négociation dans le bilan.

Nous complétons ensuite ces variables CAMELS traditionnellement utilisées dans les EWS par d'autres variables explicatives moins fréquemment rencontrées dans cette littérature. Afin de capter un possible effet *"too-big-to-fail"*, thématique qui sera abordée en profondeur dans le chapitre 2, nous incluons une mesure de la taille des établissements : le logarithme du total d'actifs. Nous cherchons également à prendre en compte globalement le modèle d'affaire de chaque établissement en mesurant la part de certaines activités au sein de leur bilan : les prêts et les titres à l'actif, les dépôts collectés et les titres émis au passif. Cela permettra de tenir compte dans les régressions du fait qu'une banque soit plus ou moins tournée vers les activités traditionnelles de collecte des dépôts et d'octroi de crédits. Par ailleurs, nous ajoutons deux mesures de liquidité interbancaire qui ont montré leur pertinence dans l'analyse de la systémicité des établissements : la part des actifs et des passifs interbancaires au bilan. Afin de prendre en compte une possible croissance excessive du crédit par le passé, nous incluons une mesure de la croissance globale du crédit. Pour finir, afin de capter l'éventuelle influence du pouvoir de marché de certains établissements et de l'effet de la compétition, nous calculons un indice de Lerner.

La stratégie économétrique utilisée est identique à celle de la grande majorité des articles de la littérature des EWS : nous appliquons une régression logistique de notre indicatrice de défaillance bancaire sur l'ensemble des variables explicatives citées précédemment avec un retard d'une année. Cela permet de déterminer parmi ces variables explicatives celles qui ont un impact significatif ex-ante (à $t-1$) sur la probabilité qu'une banque

connaisse une défaillance à t. Nos résultats montrent la pertinence globale des variables CAMELS dans l'application d'un EWS au système bancaire français. Ces variables affichent le signe attendu dans la plupart des régressions, même si toutes ne s'avèrent pas significatives. Nous montrons que le principal déterminant ex-ante de la défaillance bancaire est la rentabilité des actifs des banques, mesurée par le ROA, ainsi que sa volatilité. Toutes choses égales par ailleurs, une banque plus profitable et à la rentabilité plus stable est moins susceptible de faire face à une situation de défaillance.

De manière surprenante, les ratios d'adéquation des fonds propres (le ratio de solvabilité et le ratio de levier) n'apparaissent pas comme des prédicteurs efficaces de la défaillance bancaire. Cela pourrait être une application de la "loi de Goodhart", qui stipule que lorsqu'un indicateur devient la cible d'une mesure réglementaire, il cesse d'être une bonne mesure prédictive. Sachant que les ratios d'adéquation des fonds propres sont des indicateurs prioritaires avec des niveaux minimum à respecter impérativement dans le cadre de la réglementation prudentielle, il n'est alors pas si surprenant qu'ils aient perdu leur pouvoir prédictif dans un modèle EWS. Toutefois, lorsque nous restreignons l'analyse aux cas de défaillance les plus extrêmes (les dégradations de notation vers la note 5), alors le ratio de solvabilité devient finalement un prédicteur efficace.

Ce chapitre montre également qu'il est pertinent de prendre en compte le type de banque d'un point de vue de leur actionnariat. En différentiant les régressions entre les banques privées, publiques et mutualistes, nous cherchons à identifier si les déterminants de la défaillance sont ou non identiques entre ces types de banque. En effet, nos résultats montrent que, dans l'ensemble, les principaux facteurs ex-ante de détresse semblent varier entre ces différents types de banque en fonction de leur type d'actionnariat. La défaillance des banques privées apparaît davantage induite par la rentabilité et les indi-

Variable dépendante : indicatrice de défaillance bancaire (dégradation de la notation de la banque vers la note 4 ou 5)				
	Type de banque			
Variables	Toutes	Privées	Publiques	Mutualistes
Ratio de levier bâlois (t-1)	-0.939*			
Ratio de provisionnement (t-1)	-3.833*		-21.43**	
Coefficient d'exploitation (t-1)			1.541**	
Rendement des actifs - ROA - (t-1)	-12.029***	-12.647***		
Volatilité du ROA (t-1)	12.027***	11.063***		
Ratio de liquidité NSFR (t-1)	-0.151**			
Part des actifs à des fins de trading (t-1)	1.818			6.672***
Taille - logarithme du total d'actifs - (t-1)	-0.187***			-0.258***
Part des prêts dans le bilan (t-1)	-1.568***			-1.868***
Part des dépôts dans le bilan (t-1)				4.173***
Part des titres émis dans le bilan (t-1)		-1.968**		5.103***
Part des actifs interbancaires dans le bilan (t-1)	-1.187***	-0.847**		
Part des passifs interbancaires dans le bilan (t-1)		0.800**		2.199**
Observations (banques x années)	3,925	1,630	377	1,918
Nombre de banques distinctes	449	191	25	233

Résultats de régressions logistiques avec procédure "stepwise" et erreurs clusterisées au niveau de chaque banque. Niveaux de significativité : * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Parmi l'ensemble des variables testées comme déterminants ex-ante de la défaillance, seules les plus significatives figurent dans ce tableau de synthèse.

Table 1: Principaux résultats économétriques du chapitre 1 : caractère prédictif de certaines variables sur la probabilité de défaillance des banques

cateurs de liquidité interbancaire, tandis que pour les banques mutualistes les situations de défaillance ont tendance à être davantage prédites par la taille ou les indicateurs de risque de marché.

Alternativement, ce chapitre cherche également à déterminer les facteurs influant, non plus sur la probabilité d'occurrence d'une défaillance, mais sur la durée des épisodes de défaillance. Il s'avère que la taille des banques a un impact négatif et significatif sur la durée des événements de défaillance, ce qui signifie que, toutes choses égales par ailleurs, lorsque les grandes banques sont confrontées à une situation difficile, elles sont moins susceptibles d'entrer dans une période de défaillance de longue durée que les petites banques. La part des actifs interbancaires dans l'actif total tend également à réduire la durée de l'événement de défaillance, car cette catégorie d'actifs est généralement plus liquide que les prêts et peut être rapidement convertie en cash plus facilement pour restructurer le bilan d'une banque en difficulté.

L'efficacité de notre modèle EWS est plutôt satisfaisante puisque plus de 70% des observations sont correctement classifiées un an à l'avance en prévisions "in-sample" et il conserve une bonne efficacité pour les prévisions "out-of-sample". Néanmoins les limites d'un tel modèle illustrent également qu'il subsiste une dimension discrétionnaire dans l'évaluation faite par le superviseur. Sur la base de leurs connaissances approfondies de l'activité des banques, les superviseurs bancaires sont en mesure de prendre en compte divers autres éléments dans la notation finale qui reflète la situation globale de la banque évaluée. En termes d'implications, ce chapitre illustre la pertinence d'utiliser un modèle EWS dans le cas français comme base ou complément de l'évaluation discrétionnaire de la situation individuelle des banques effectuée par l'autorité de supervision.

Nous introduisons désormais la deuxième thématique de cette thèse, celle du risque systémique. Partiellement présente dans le premier chapitre de par la prise en compte d'un possible effet *"too-big-to-fail"* sur la probabilité de défaillance (justifiant la prise en compte de la taille des banques comme variable de contrôle dans les régressions), cette thématique sera au cœur du chapitre 2.

Le risque systémique dans le système bancaire

Les banques dites systémiques sont définies comme celles dont "la détresse ou la faillite désordonnée pourrait causer des perturbations significatives au système financier dans son ensemble ainsi qu'à l'activité économique" (FSB [2011]). Lors du sommet de Pittsburgh en 2009, les dirigeants du G-20 ont appelé les régulateurs à proposer des solutions au problème posé par ces banques "trop grosses pour faire faillite" (*too-big-*

to-fail - TBTF). Cette catégorie de banques avaient déjà été explicitement identifiées dès 1984 aux États-Unis, et l'aléa moral lié à leur statut a commencé à être analysé par la littérature académique depuis longtemps (Flannery and Sorescu [1996]; Freixas et al. [2004]). Toutefois, aucune mesure concrète destinée à mettre fin aux distorsions TBTF n'avait été prise avant que la crise de 2008 n'éclate.

La crise financière de 2008 a clairement révélé que la taille n'est qu'un déterminant de la systémicité : la complexité des activités d'une banque, ses interconnexions avec d'autres entités financières, ainsi que ses activités à l'international sont d'autres dimensions clés du risque systémique. Depuis, la quantification de l'empreinte systémique des banques et l'identification des institutions financières systémiques sont devenues des priorités pour les régulateurs internationaux dans un contexte de réformes post-Lehman Brother. De nombreuses mesures de l'empreinte systémique des grandes banques ont été proposées dans la littérature académique, principalement basées sur des données de marché, notamment les mesures CoVaR (Adrian and Brunnermeier [2016]), SRISK (Acharya et al. [2012] and Engle et al. [2015]) ou encore le *Marginal Expected Shortfall* (Acharya et al. [2017]). Parallèlement, en utilisant principalement des informations comptables et prudentielles, les régulateurs internationaux ont développé des réglementations spécifiques pour mieux encadrer les institutions financières, les rendre plus résilientes et mettre fin au problème du *too-big-to-fail*.

Dans ce but, le concept de "banque d'importance systémique mondiale" (G-SIB - *global systemically important bank*) a été introduit dans la régulation bancaire internationale des accords de Bâle III pour caractériser les banques présentant la plus forte empreinte systémique à l'échelle mondiale et qui seraient désormais soumises à une réglementation, une surveillance et un régime de résolution plus stricts. La publication de la première liste des G-SIB par le Conseil de stabilité financière (*Financial Stabil-*

ity Board - FSB) a eu lieu en novembre 2011. Elle est depuis révisée chaque année. Les banques figurant sur cette liste sont donc sujettes à des mesures réglementaires ciblées, avec notamment des exigences de fonds propres dédiées (coussins de fonds propres supplémentaires), des exigences renforcées en termes d'absorption des pertes, des mesures macroprudentielles, et des contraintes supplémentaires en matière de résolution. Au sein de la liste des G-SIBs, les banques sont réparties par sous-catégories (ou *"buckets"*) de systémicité croissante, introduisant ainsi un degré de proportionnalité et imposant des exigences de fonds propres additionnelles de plus en plus contraignantes à mesure que la systémicité de la banque s'accroît. Les graphiques ci-dessous illustrent la méthodologie définie par la réglementation bâloise pour déterminer la systémicité des banques et établir chaque année la liste des G-SIBs.

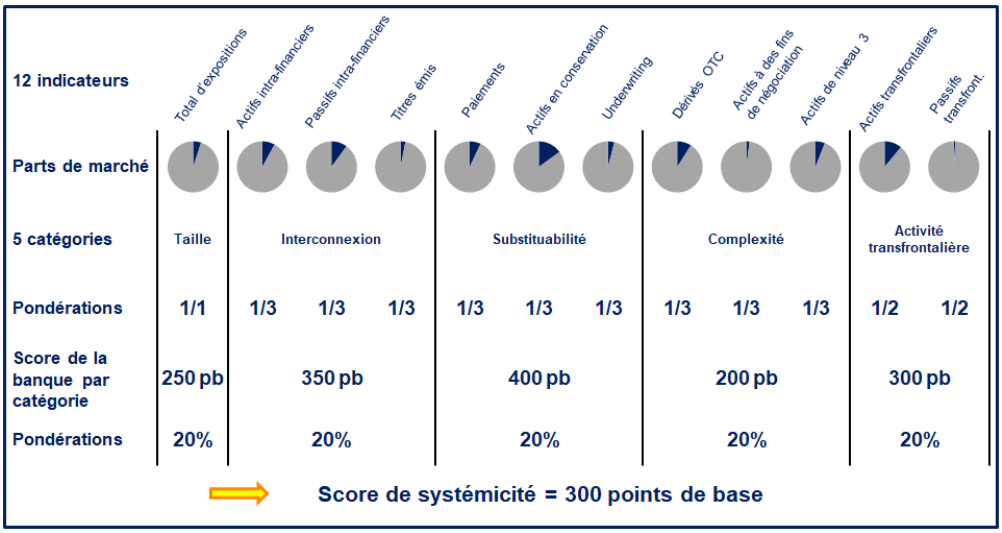

Figure 7: Illustration du calcul du score de systémicité bâlois

La littérature académique récente a poursuivi l'analyse de cette thématique de la systémicité bancaire en suivant plusieurs voies de recherche. Certains articles se concentrent sur le sujet de la calibration optimale des coussins de fonds propres imposés à ces banques systémiques (Passmore and von Hafften [2017]), d'autres tentent d'évaluer

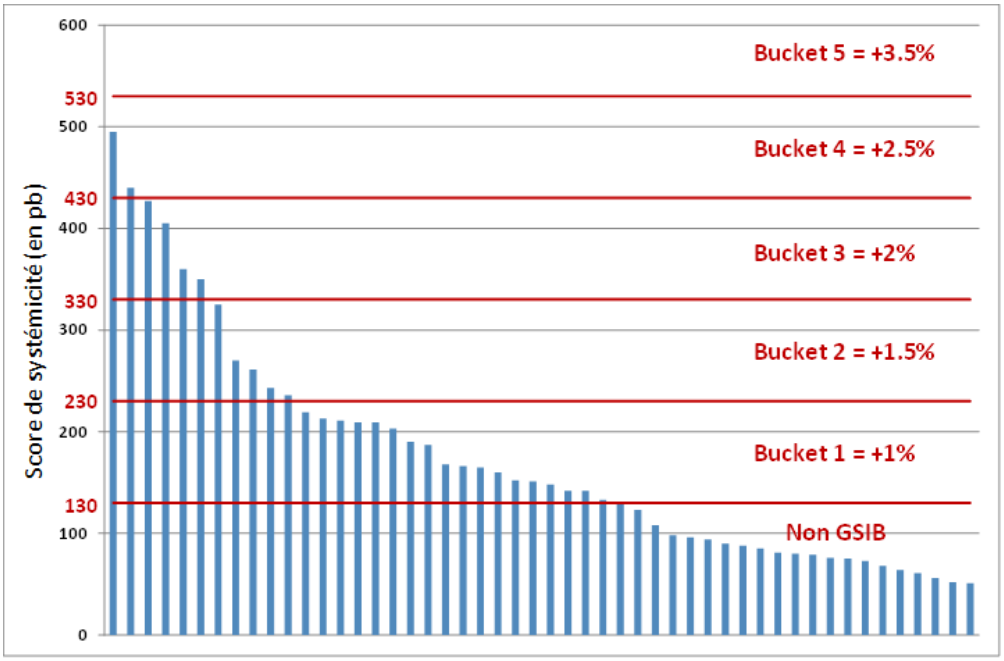

Figure 8: Illustration de la répartition des banques systémiques par "buckets"

l'impact de cette réglementation sur les valorisations boursières des entités concernées (Moenninghoff et al. [2015]) ou sur les garanties implicites dont disposent ces banques systémiques (Schich and Toader [2017]). Toutefois, pour autant que je sache, aucun article ne proposait d'évaluation empirique globale de l'impact de cette nouvelle réglementation sur l'activité des banques concernées. C'est donc dans cette optique que s'inscrit le chapitre 2 de cette thèse.

L'impact de la désignation des banques d'importance systémique mondiale sur leur activité (chapitre 2, co-écrit avec Dominique DURANT et Oana TOADER)

Ainsi, afin de combler cette lacune de la littérature exposée précédemment, le chapitre 2 de cette thèse cherche à évaluer si ces réformes réglementaires dédiées aux banques

systémiques ont contribué aux objectifs du G-20 de renforcer la résilience des institutions financières et d'améliorer la stabilité financière mondiale. Plus précisément, nous évaluerons si les banques désignées comme G-SIB ont subi des changements conformes aux objectifs visés, et quantifierons ces impacts. Nous chercherons également à déterminer si certaines conséquences imprévues (ou non recherchées par la réglementation) se sont également produites.

Afin de mener cette étude, nous exploitons les données comptables (relatives au bilan et au compte de résultat) de 97 grandes banques, réparties dans 22 pays sur la période 2005-2016 (12 ans), dont 34 ont déjà été identifiées au moins une fois comme G-SIB sur la période. Pour chaque banque, nous avons collecté un ensemble de variables à fréquence annuelle au moyen de la base de données S&P Global Market Intelligence. Une première série d'indicateurs collectés porte sur la composition du bilan et les ratios prudentiels, avec notamment le taux de croissance du total des actifs, deux ratios de fonds propres (ratio de levier et ratio de solvabilité pondéré), la part de trésorerie dans le total des actifs, la part des prêts à la clientèle non financière dans l'actif total, et la part de la dette subordonnée dans le total des passifs. Une seconde série d'indicateurs comprend des mesures de rentabilité (rendement des actifs - ROA - et rendement des capitaux propres - ROE), des indicateurs de prise de risque (la densité de RWA, le ratio de prêts non performants) et des taux de rendement (rendement des prêts, coût moyen des dépôts et marge nette d'intérêt). Chacune de ces variables sera utilisée comme variable dépendante dans les régressions.

Comme énoncé précédemment, ce chapitre vise à évaluer les changements qui ont affecté les banques suite à leur désignation en tant que G-SIB. Avec un tel objectif à l'esprit, nous nous appuyons sur une approche inspirée de la méthodologie dite "différence de différence". Dans une analyse standard de ce type, le groupe de G-SIBs correspondrait

au *groupe traité*, tandis que le groupe des autres banques (ci-après les "non-G-SIBs") constituerait le *groupe de contrôle*. La stratégie d'identification économétrique retenue nous permet d'évaluer l'impact de la désignation des G-SIBs sur leur activité : elle permet de capturer l'impact causal de la désignation sur une variable donnée pour les G-SIBs, en contrôlant d'une part les éventuelles différences structurelles entre les G-SIBs et les non-G-SIBs, et d'autre part les changements structurels au cours du temps (ou "tendances sectorielles").

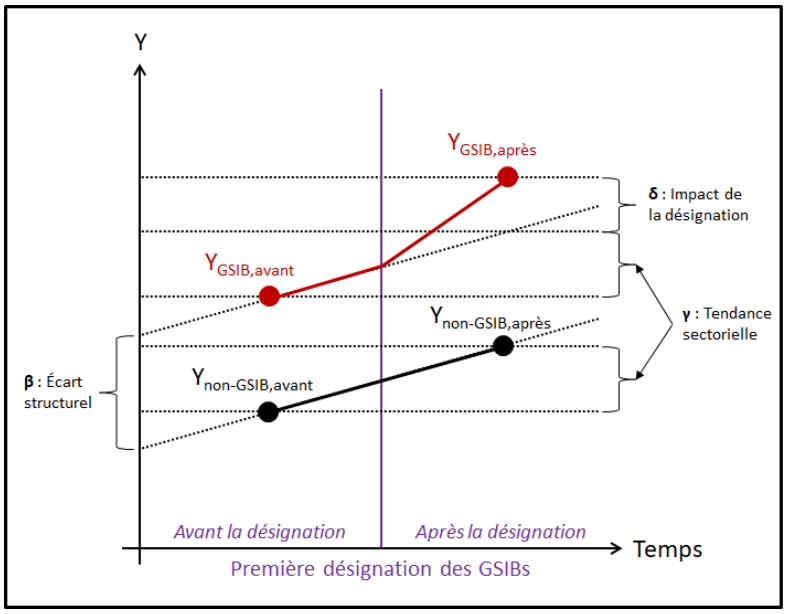

Figure 9: Illustration simplifiée de la méthodologie appliquée dans le chapitre 2

Dans un premier temps, le modèle permet d'identifier des différences structurelles initiales entre les G-SIBs et les autres banques. À cet égard, nous montrons que les G-SIBs ont un levier financier structurellement plus haut (donc un ratio de levier bâlois structurellement plus bas). Nous trouvons également des preuves empiriques que les G-SIBs bénéficient d'un coût de financement plus faible que celui des autres banques, ce qui est susceptible d'indiquer un risque idiosyncratique plus faible, en raison d'une plus grande diversification ou en raison d'une garantie publique implicite.

Dans un second temps, nous identifions les changements qui ont affecté les G-SIBs suite à leur première désignation par le FSB en 2011. À partir de ces résultats quantitatifs nous pouvons donc fournir une première évaluation de l'efficacité des réformes dédiées aux G-SIBs instaurées après la crise de 2008 et déterminer si les changements mis en évidence sont conformes aux objectifs initiaux des régulateurs internationaux. Ce deuxième chapitre de la thèse montre donc que certains objectifs visés ont été atteints : l'expansion du bilan des G-SIBs a été considérablement ralentie par la réglementation. Le levier financier des G-SIBs, structurellement supérieur à celui des autres banques avant la désignation, a également été significativement réduit. Cette augmentation de la base de fonds propres des G-SIBs a renforcé leur résilience, ce qui contribue positivement à la stabilité financière mondiale. Cependant, cette réduction du levier financier des G-SIBs (*"deleveraging"*) a conduit à une autre conséquence logique, bien que non spécifiquement recherchée par la réglementation : la réduction de leur rendement des fonds propres (ROE), par un effet de mécanique comptable.

	Paramètres		
Variables dépendantes successives :	β Écart structurel	γ Tendance sectorielle	δ Impact de la désignation
Taux croissance annuel du bilan	0,177	-1,651**	**-5,763*** **
Ratio de levier (tier 1 sur total d'actifs)	-0,907**	0,509***	**0,589*** **
Part de la trésorerie dans le bilan	-0,300	2,312***	**2,340*** **
Part des crédits à la clientèle dans le bilan	-4,475	3,555***	**-1,120**
Part des dettes subordonnées émises	0,294	-0,234	**0,301***
Rendement des actifs (ROA)	-0,024	0,157***	**-0,074**
Rendement des fonds propres (ROE)	1,782	1,853**	**-3,064*** **
Densité des RWA	-3,784	-2,714**	**4,609*** **
Coût de financement	-0,418**	-0,122	**0,086**

Résultats de régressions en "différence de différence" appliquées sur un panel de 97 grandes banques dont 34 déjà été identifiées au moins une fois comme G-SIB. Chiffres exprimés en points de pourcentage. Niveaux de significativité : * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Parmi l'ensemble des variables dépendantes testées, seules les plus pertinentes figurent dans ce tableau de synthèse.

Table 2: Principaux résultats économétriques du chapitre 2 : impacts de la désignation des G-SIBs

Par ailleurs, nous montrons dans ce chapitre que les éventuelles conséquences négatives

involontaires de ces réglementations, qui avaient été signalées soit via des considérations théoriques, soit via les craintes exprimées par l'industrie, ne se sont au final pas matérialisées. En effet, pour l'instant, nous n'avons identifié aucune réduction de l'offre de crédit à l'économie, ni de prise de risque excessive de la part des banques en quête de rendements supérieurs, qui pourraient être attribuées à ces réglementations. Pour finir, le chapitre souligne que l'avantage en termes de coût de refinancement que les G-SIBs tirent des garanties publiques implicites semble persister au regard des données disponibles. Il semble donc que l'objectif de mettre fin à l'ensemble des distorsions induites par le statut de *"too-big-to-fail"* n'est pas encore totalement atteint.

Si la systémicité des banques et la mise en œuvre de contraintes réglementaires spécifiques ne semblent pas avoir eu d'impact sur le financement de l'économie, en revanche la distribution du crédit s'avère affectée, non seulement par la conjoncture macroéconomique, mais également par la typologie des banques au niveau de leur actionnariat. C'est l'objet de la troisième thématique de cette thèse que nous introduisons dans la section suivante et qui fera l'objet du chapitre 3.

La cyclicité du crédit et la substitution banques publiques - banques privées

Comme illustré par le graphique ci-dessous, la distribution du crédit en France (comme dans les autres pays) présente un degré de cyclicité étroitement lié au cycle économique. Le taux de croissance du crédit à une période donnée s'avère très fortement influencé par les conditions macroéconomiques des quelques périodes antérieures. Au niveau agrégé, cela montre que les banques adaptent leur octroi de crédit à la conjoncture, soit de leur

propre initiative en restreignant leur offre de crédit, soit du fait d'une réduction de la demande de crédit de la part de leur clientèle. L'analyse des raisons de cette cyclicité n'est pas l'objet central de cette thématique, en revanche nous nous intéressons à la question suivante : existe-t-il des disparités entre types de banque dans leur adaptation de la distribution du crédit au cours du cycle économique ? En particulier, la question s'est déjà régulièrement posée dans la littérature sur le rôle joué en la matière par les banques publiques et les banques privées.

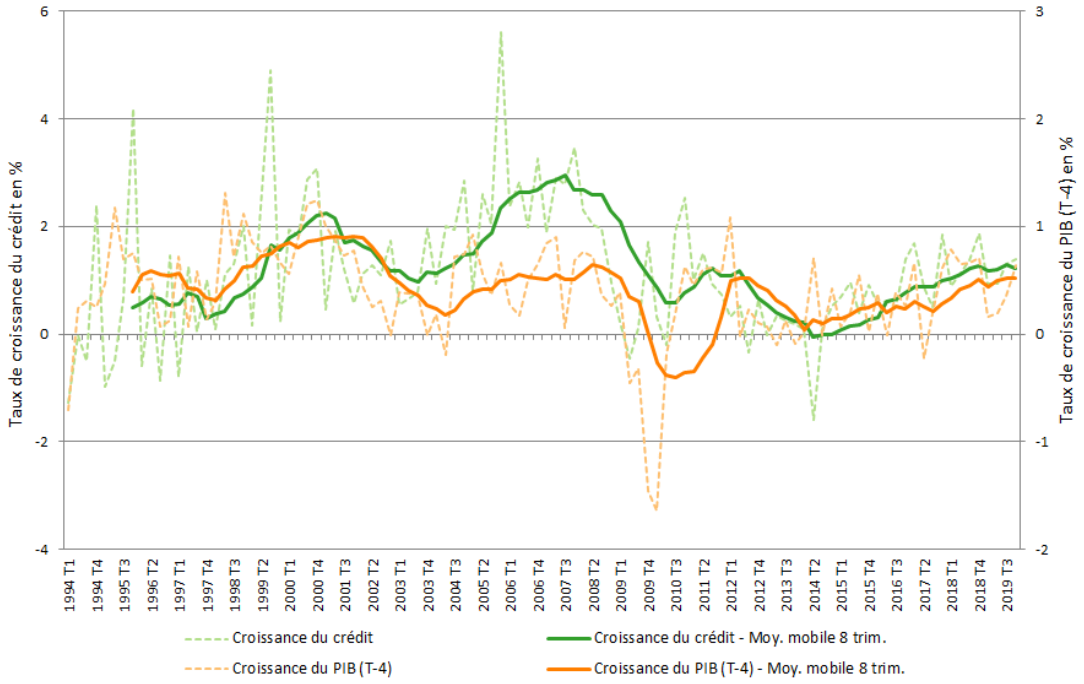

Figure 10: Croissance trimestrielle du crédit et du PIB en France

Cette thématique des banques publiques se substituant partiellement aux banques privées pour le financement de l'économie a plusieurs fois été analysée dans la littérature d'un point de vue théorique et empirique. Théoriquement, comme le résume bien Brei and Schclarek [2015], cette substitution partielle peut s'expliquer par diverses raisons. Tout d'abord, il y aurait un effet lié à l'internalisation des conséquences

macroéconomiques de leur octroi de crédit par les banques publiques, qui contrairement aux banques privées privilégieraient moins la maximisation des bénéfices, et donc seraient plus disposées à soutenir l'économie en période de crise, quitte à prendre des risques pouvant se traduire par des pertes futures. Par ailleurs, les banques publiques peuvent bénéficier d'un accès facilité au refinancement du fait de leur lien avec l'État, et seraient également moins susceptibles de connaître des épisodes de retraits massifs de dépôts, ne limitant donc pas leur capacité à prêter, même en période de forte turbulences économiques ou financières. Empiriquement, cette substitution partielle entre banques publiques et banques privées a bien été constatée, que ce soit avec des panels internationaux de banques (voir notamment Micco and Panizza [2006], Cull and Martinez Peria [2013], Brei and Schclarek [2013] et Bertay et al. [2015]), ou en étudiant un système bancaire national (voir par exemple Leony and Romeu [2011], Lin et al. [2012], Behr et al. [2017] ou encore Jimenez et al. [2018]).

Cette question du comportement respectif des banques privées et des banques publiques peut également se poser dans le cas du système bancaire français, où les banques publiques occupent une place non négligeable et qui s'est même accrue ces dernières années. Suite aux difficultés rencontrées par le groupe bancaire franco-belge Dexia, sa filiale en France (Dexia Municipal Agency) a été cédée en janvier 2013 à la "Société de Financement Local" (SFIL), banque publique détenue principalement par l'État français. La restructuration de ce groupe bancaire public a eu notamment pour objectif de pérenniser le financement des collectivités locales, ce qui constitue la principale ligne d'activité du groupe. Au même moment, la loi du 31 décembre 2012 officialisait la création de la "Banque publique d'investissement". Aujourd'hui connu sous le nom "BPI France" ou "Groupe BPI", ce nouveau groupe bancaire est issu du rapprochement d'OSEO, de CDC Entreprises et du Fonds stratégique d'investissement (FSI). À l'inverse de la SFIL dont la clientèle cible est principalement constituée d'entités publiques, BPI

France se donne pour mission de renforcer le financement des PME et ETI françaises. Ces deux événements illustrent une volonté d'assurer la solidité et l'efficacité d'acteurs publics de financement de l'économie en France, dans un contexte macroéconomique alors caractérisé par une faible croissance et par un supposé resserrement du crédit de la part des banques commerciales privées. L'objectif affiché par ces banques publiques est donc de jouer un rôle contra-cyclique de financement de l'économie et d'agir sur les imperfections de marché.

Plus récemment, alors que la crise due à la pandémie de COVID-19 se propageait début 2020, le ministère français des Finances a décidé d'apporter la garantie de l'État sur les nouveaux prêts accordés par les banques aux entreprises afin d'éviter un resserrement du crédit. Ces prêts garantis par l'État pourraient atteindre jusqu'à 300 milliards d'euros. Dans ce dispositif la Banque Publique d'Investissement (BPI) a joué un rôle opérationnel clé dans la mise en œuvre du plan de soutien gouvernemental aux entreprises. Cela attire donc l'attention sur l'importance relative des différents types de banque en France et pose la question de leurs comportements d'octroi de crédit respectifs en temps de crise.

À notre connaissance, cette thématique de la possible asymétrie d'octroi de crédit entre banques privées et banques publiques n'a jamais été explorée empiriquement dans le cas du système bancaire français, ce qui constituera la première contribution du troisième chapitre de cette thèse.

L'octroi de crédit aux entreprises par les banques privées, mutualistes et publiques au cours du cycle économique : le type de banque importe-t-il ? (chapitre 3)

L'objectif du troisième chapitre est donc d'investiguer les éventuelles asymétries entre banques privées et banques publiques en France quant à leur octroi de crédit, à l'image de ce qui se trouve dans la littérature académique. Toutefois, contrairement à la plupart des articles de la littérature qui se concentrent sur cette dichotomie usuelle entre les banques publiques et privées, nous adaptons ici la problématique à l'une des spécificités du système bancaire français : la présence notable d'acteurs bancaires "mutualistes". Bien qu'elles soient des banques privées, en ce sens qu'elles n'appartiennent pas à des entités publiques, ces banques mutualistes diffèrent des banques "privées" habituelles à bien des égards, et notamment en termes de gouvernance et d'actionnariat, puisque les "actionnaires" des groupes mutualistes sont désignés comme des "sociétaires" et sont en même temps des clients de ces banques. Cette structure particulière pourrait donc aboutir à une politique d'offre de crédit différente et qui justifie de les analyser séparément.

Nous avons constitué une base de données très granulaire permettant de suivre l'évolution à fréquence trimestrielle, entre 1999 et 2019, des encours de crédit à un niveau banque-entreprise pour l'ensemble des relations dépassant un encours cumulé de 76 000 euros. Cette base très extensive est volontairement restreinte à un type d'entreprise bien particulier : celles qui sont en permanence en lien avec au moins deux types de banque parmi les trois que nous avons définis (privée / publique / mutualiste). En limitant notre panel à ces entreprises "multi-bancarisées" (*"multi-bank-type firms"*) nous pouvons ainsi assurer que la demande de crédit entre les différents types de banque est très homogène. Il en résulte un panel de plus d'un million d'observations portant sur 13 125 entreprises distinctes et sur 276 banques distinctes. Par ailleurs, afin de contrôler

encore mieux l'hétérogénéité entre les entreprises, nous leur ajoutons des variables de contrôles spécifiques, comme leur appartenance à un secteur d'activité, ou encore leur notation Banque de France évaluant la qualité de leur signature. En assurant que les effets de demande sont bien pris en compte, ce panel permet donc de mieux identifier ce qui relève des effets d'offre de crédit.

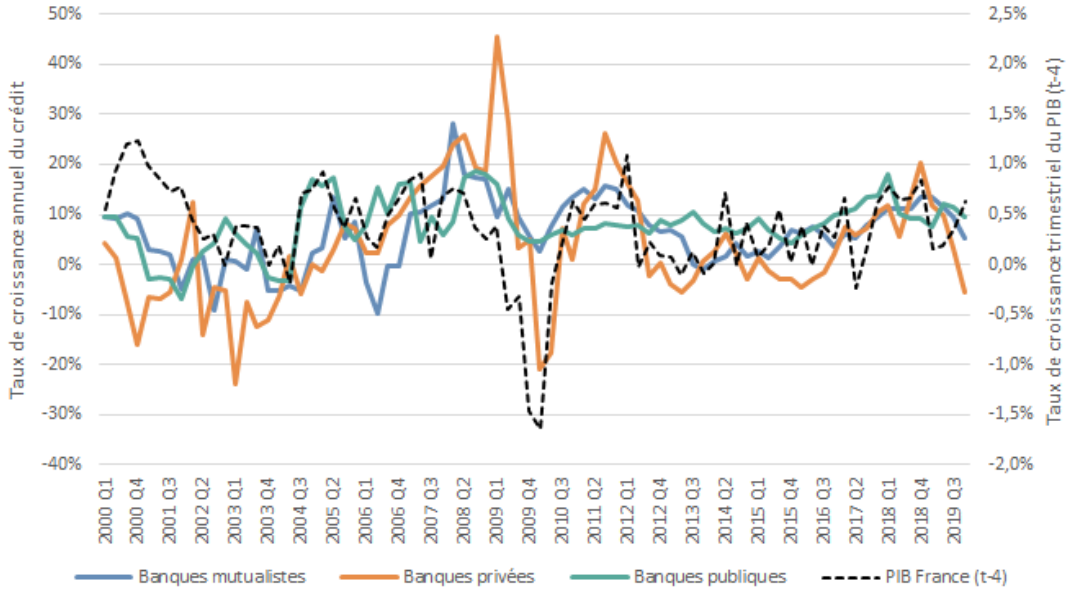

Figure 11: Cyclicité du crédit aux entreprises "multi-bancarisées" par type de banque

Nous avons par ailleurs collecté des variables macroéconomiques, telles que les taux d'intérêts réels ou le taux de chômage, qui pourront servir de variables de contrôle globale. Mais surtout nous utilisons le taux de croissance trimestriel du PIB français pour définir trois critères de "crise". Le premier critère "C1" est une variable binaire prenant la valeur 1 lorsque le taux de croissance du PIB devient négatif (avec un décalage de 4 trimestres). Un deuxième critère "C2", lui aussi binaire, prend la valeur 1 uniquement lorsque l'économie française entre en récession (toujours avec un décalage de 4 trimestres), ce qui revient à restreindre le critère "C1" à l'épisode de plus intense dif-

ficulté qu'ait connu l'économie française entre 1993 et 2019, soit la période 2008-2009. Un troisième critère "C3", continu quant à lui, prend simplement pour valeur l'opposée du taux de croissance du PIB (toujours avec 4 trimestres de décalage).

La spécification économétrique choisie permet aux coefficients de varier en fonction de la typologie de banque et de la situation économique globale reflétée alternativement par l'un de nos trois critères C1/C2/C3. Économétriquement, plusieurs variables de contrôle mesurées au niveau des banques sont également collectées afin d'éliminer certains biais dans les régressions : la taille du bilan, la situation de l'établissement en termes de liquidité et solvabilité, la rentabilité de l'établissement, la part d'actifs dépréciés au bilan, la dépendance de l'établissement vis-à-vis du refinancement de marché, etc. Avec ces régressions il est alors possible de conclure sur d'éventuelles asymétries significatives d'octroi de crédit aux entreprises entre ces types de banque au cours du cycle économique.

Nos résultats montrent que, suite à une entrée de la croissance du PIB en territoire négatif (C1), on observe une réduction du taux de croissance annuel du crédit de -0,9 point de pourcentage (pp) pour les banques privées. Les banques mutualistes affichent une évolution du crédit moins procyclique avec une réduction de "seulement" -0,4 pp, tandis que les banques publiques semblent réagir de manière contracyclique puisque leur octroi de crédit s'en trouve accru de 1,3 pp. Lorsque l'on se concentre sur la période de récession de 2008-2009 (C2), on observe que le taux de croissance annuel du crédit au niveau banque-entreprise se réduit de 3,3 pp dans le cas des banques privées en période de récession, alors que la réduction est deux fois moins prononcée pour les banques mutualistes (-1,6 pp). En revanche, dans le cas des relations banque-entreprise avec les banques publiques, le taux de croissance du crédit ne semble pas être impacté de manière significative par la récession.

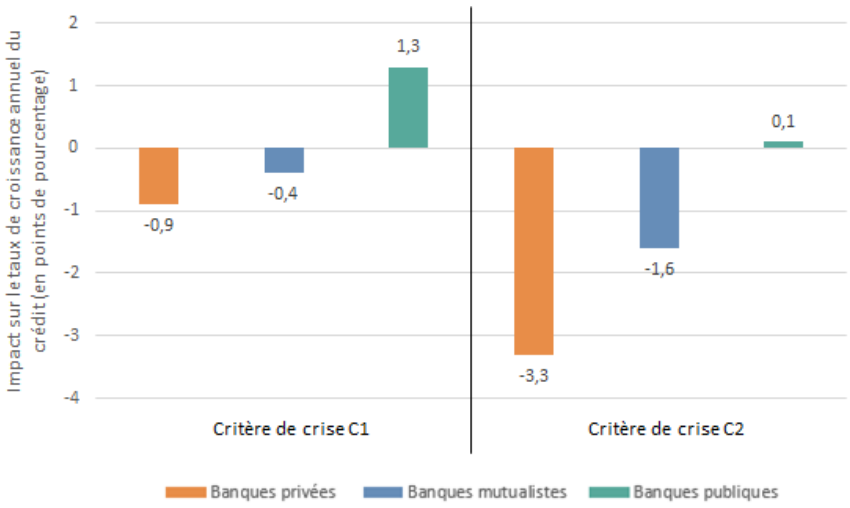

Figure 12: Principaux résultats économétriques du chapitre 3 : impact des critères de crise sur l'octroi de crédit aux entreprises "multi-bancarisées"

D'une manière générale, en utilisant notre troisième critère de crise (C3), nous constatons qu'au cours du cycle économique, l'offre de crédit aux entreprises non financières par les banques privées a tendance à être procycliques car elle se développe plus rapidement pendant les périodes de forte croissance et s'avère plus impactée par des turbulences macroéconomiques. Dans le cas des banques mutualistes, l'octroi de crédit apparaît également procyclique, mais nettement moins que dans le cas des banques privées, tandis que les banques publiques présentent une offre de crédit globalement acyclique.

Ces résultats sont corroborés par l'analyse de la dynamique du crédit au niveau plus agrégé de chaque entreprise (et non plus au plus fin niveau de la relation banque-entreprise) : nous montrons empiriquement qu'une plus grande proportion du financement reçu de la part des banques publiques et/ou mutualistes tend à réduire la procyclicité du crédit total de l'entreprise. Pour finir, nous faisons appel à une seconde base de données bien moins granulaire car le crédit y est mesuré au niveau de chaque banque, mais en revanche bien plus étendue car les encours de crédit concernent alors l'ensemble

des emprunteurs (ménages, administrations, etc.) et non plus seulement les entreprises. Les résultats obtenus avec ce second panel sont totalement en phase avec ceux énoncés ci-dessus.

En termes d'implications, l'intérêt de ce troisième chapitre de la thèse est double. Au niveau macroéconomique, la connaissance de ces asymétries d'octroi de crédit entre types de banque est importante pour l'analyse du financement de l'économie en période de crise et la mise en œuvre de mécanismes de soutien. Cette thématique est donc particulièrement redevenue d'actualité en 2020. Au niveau microéconomique, dans une perspective de finance d'entreprise, nos résultats mettent en lumière l'importance de diversifier les sources de financement et de développer des relations avec des banques de différents types qui adopteront des comportements d'octroi de crédit différenciés au cours du cycle économique.

Les trois chapitres qui suivent développent en détails les travaux introduits ci-dessus.

*

* *

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Chapter 1.

An Early Warning System based on French Banks Supervisory Rating and Financial Ratios

Aurélien VIOLON

An Early Warning System based on French Banks Supervisory Rating and Financial Ratios

Aurélien Violon*

April 11th, 2021

ABSTRACT:

This paper provides an empirical assessment of the relevance of an early warning system for the French banking sector. It builds on an innovative data source to identify "distressed" banks, relying on an internal supervisory rating. We apply the usual multivariate logit regression methodology on a set of CAMELS variables commonly used in the literature that we complement with additional bank-specific indicators, such as inter-bank liquidity variables. Our results bring general support to the usual set of CAMELS variables for the French banking sector and show the key role of profitability level and volatility as predictors of distress. Surprisingly, capital adequacy ratios do not appear as very efficient predictors, which might be an application of "Goodhart's law". We also take into account the different types of bank, and especially the presence of some "cooperative" banks, which is a key characteristic of the French banking sector, and find evidence that drivers of vulnerability differ across banks depending on their ownership. Private banks' distress appears more driven by profitability and inter-bank liquidity metrics, while cooperative banks' distress situations tend to be more predicted by size or market risk metrics. Finally, we notice that the efficiency of our EWS models is rather satisfying as more than 70% of observations are correctly classified one year ahead, but this also reveals that there is a remaining discretionary dimension in the assessments made by banking supervisors.

JEL classification: G01, G21, G28, G33

Keywords: Bank distress, Early Warning System (EWS), CAMELS, French banking sector, Supervisory rating

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1 Introduction

Bank failures can have dramatic effects both for the financial sector and for the whole economy, especially in the case of systemic banks, as emphasized by the bankruptcy of Lehman Brothers in 2008 and the macroeconomic consequences of the great financial crisis. Therefore, being able to predict banks' failure, or at least better identify ex-ante drivers of banks' vulnerability appears of major interest, both from a banking supervisor's microprudential perspective and from a policy-maker's macroeconomic point of view. This is the purpose of a class of models referred to as *"early warning systems"* (hereafter "EWS").

A large majority of existing EWS papers either focus on US banks or on international panels of large banks. To the best of our knowledge, the efficiency of an EWS mostly based on the usual set of "CAMELS" variables has never been tested specifically for the whole French banking sector. This is precisely the purpose of this paper. The French banking sector is characterized by several specificities that require special attention. First, four out of the 30 global systemically important banks (G-SIBs) - and out of the eight euro area G-SIBs - are headquartered in France. But on top of these four G-SIBs, the French banking sector is rather concentrated (much more than the US banking system), which makes it sensitive to a potential bank failure. Therefore being able to predict failures, or at least identify sources of vulnerability is of paramount importance. Second, the French banking sector has a diversity of banks in terms of type of ownership. Besides the usual dichotomy between private and state-owned banks, France has three networks of "cooperative banks" that legally and economically differ from private banks. Being able to take into account the potential impacts of these ownership differences is necessary, as drivers of distress may not be the same for all banks. Finally, contrary to the US banking system, the French banking sector shows almost no failure, but French banks are obviously not free of vulnerabilities. This mostly comes from the fact

that the French supervisory authority usually intervenes ex-ante and forces banks to take corrective actions before failure occurs, while in the USA, supervisors more easily let some banks fail. The relative absence of failures in the French banking sector is fortunate for depositors, but much less for researchers trying to assess sources of banks vulnerability, as they need a broader definition of "bank distress" than pure economic failure.

The definition of the dependent variable is the most crucial issue in this literature and it can differ drastically from one paper to another. Some use legal definition of bankruptcy, other rely on market-based metrics, while other define thresholds on accounting values. In this paper we rely on an innovative source of information. The French prudential and resolution authority has been using an internal rating methodology between 1997 and 2013 to score banks' situation. Using this common methodology and all available sources of quantitative and qualitative information they have on banks (i.e. the recurring quantitative prudential reporting, some internal documents of the banks, periodic interviews with the bank's senior management, on-site inspections, etc.), banking supervisors have been assessing banks' situation at least once a year. One of the final outputs of this assessment was an overall score between 1 and 5. Using this supervisory rating output to define "distressed" banks has the advantages to enable us to broaden the definition of distress, and to give us insider information on banks health, which is particularly well suited for such an early warning model. Therefore, the aim of this paper is to identify the main drivers of banks vulnerability (as assessed by the French supervisor), rather than predict "real" bankruptcies in the legal sense.

Like most papers in this literature, we collect a set of usual "CAMELS" variables, taking into account data at the highest level of consolidation for each entity in our panel. We notice that some papers add specific variables on top of the set of CAMELS, depending on their focus (e.g. non-traditional banking activity for DeYoung and Torna [2013], or house price indexes for Zhichao et al. [2014]). Similarly, in this paper, we add

to the CAMELS variables other bank-specific characteristics that are not often taken into account in the EWS literature. We include two inter-bank liquidity variables: the share of inter-bank assets and inter-bank liabilities within total assets/liabilities. The inclusion of these variables seems particularly relevant as shocks can be transmitted through inter-bank operations, therefore they should be taken into account when assessing banks' vulnerability. We also complement our set of control variable with a measure of market power to capture the effect of competition, in the spirit of Fungàcovà and Weill [2013] that uses the Lerner index to measure the degree of bank competition and estimate its impact on the occurrence of bank failures, in the case of Russia. As that paper shown, the intensity of competition can have an effect on bank failures (tighter competition increases the occurrence of failures), therefore it is relevant to include a measure of bank market power when assessing its probability of distress. Note that our dataset only relies on accounting and prudential data, but does not include any market-based information. Indeed, such approach would not fit our population of French banks, since most of them are not publicly listed and traded on the market, which limits the availability of market data. We end up with an unbalanced panel at yearly frequency from 1997 to 2013 that contains 449 distinct banks and 5,042 bank-year observations - of which 224 situations of distress.

We apply the usual logit regression methodology and regress our "distress" variable on our set of CAMELS and control variables. This paper brings general support to the set of CAMELS variables in the context of the French banking sector. It also highlights the key importance of profitability, measured by the return on assets - ROA, both in level and volatility, to predict distressed situations. Besides the set of CAMELS, we find empirical evidence that banks' size and inter-bank liquidity are relevant determinants of distress in the case of French banks. Moreover, we find that the main ex-ante drivers of distress seem to vary across our different types of bank depending on their ownership: private banks' distress appears more driven by profitability and inter-bank liquidity

metrics, while cooperative banks' distress situations tend to be more predicted by size or market risk metrics. The main contribution of this paper is to apply an early warning system model to the specific case of the French banking sector, taking into account its specificities, both in terms of variety of banks' ownership and in terms of definition of banks' distress based on an innovative data source: the internal bank ratings of a supervisory agency.

The remainder of this paper proceeds as follows. Section 2 briefly reviews the EWS literature. Section 3 provides a comprehensive description of our dataset, notably the definition of the "distress" variable and the set of explanatory variables used in our logit regressions. The main econometric results of this study are displayed and commented on in section 4, as well as the efficiency of this EWS model. Section 5 introduces a breakdown by type of bank. Section 6 provides some robustness checks, while section 7 shows an alternative approach using the duration of distress events as main variable. Finally, section 8 concludes.

2 A short history of early warning systems

Starting in the late 1970s, a new strand of literature applied logistic regression technics to identify ex-ante determinants of banks' failures. These first papers were mostly from FED researchers and based on US banks data (see for instance Martin [1977], Hanweck [1977], Hanweck and Avery [1984], Barth et al. [1985] and Pantalone and Platt [1987]). The strategy of such early warning papers is to define a binary dependent variable taking value 1 for failed/distressed banks, and regress it (using a logit regression) on a set of lagged explanatory variables that could potentially predict distress events. Over the development of this strand of literature, six usual subsets of explanatory variables

have been identified and are commonly referred to as the "CAMELS" variables, after the name of the FDIC's rating system launched in the late 1970s and based on these variables. Each of those six subsets of variables assesses a particular dimension of banking risk: (C)apital adequacy, (A)ssets quality, (M)anagement quality, (E)arning ability, (L)iquidity situation and (S)ensitivity to market risk. Other 1990s papers brought additional support to these accounting-based models used to predict banks distress events (for instance, Thomson [1991], Cole and Gunther [1995] and Cole and Gunther [1998]), and similar approaches applying multivariate logit model at a macro banking system level have been applied (see Hardy and Pazarbasioglu [1998] or Demirgüc-Kunt and Detragiache [1999]).

Following the global financial crisis that occurred in 2007-2008 which saw many banks failing or being rescued by State interventions all over the world, there has been a renewed interest for this topic of early warning systems (EWS) and many recent papers were added to this literature. For instance, Mayes and Stremmel [2014] uses a large dataset of more than 16,000 US banks between 1992 and 2012. They identify 579 "troubled" banks over the period that either failed or received assistance from the FDIC. The paper provides a nice and complete description of the CAMELS set of explanatory variables that we will also use in this paper, as well as a broad review of previous papers on EWS. They apply two main estimation technics: a multivariate logit regression model and a survival time analysis. They found that most CAMELS variables are good predictors of bank failure or survival time horizon. Cole and White [2011] also brings support to the CAMELS approach and finds that most regressors have a significant expected sign in their logit regressions on a US commercial banks panel.

In the vein of Flannery [1998] that was one of the first to use market data, Miller et al. [2015] also builds an EWS for US bank holding companies but mostly relying on market-based indicators, such as yield spreads and expected default frequencies. Blundell-Wignall and Roulet [2013] and Zhichao et al. [2014] apply similar approaches on

an international panel of banks and use a "distance-to-default" market-based measure.

Using European data, Betz et al. [2014] develops an EWS based on 546 EU banks between 2000Q1 and 2013Q2. They include usual CAMELS variables in the regressions and also add country-level control variables since it is an international panel. Interestingly, they point out that they deliberately do not use market-based indicators (contrary to other papers like Miller et al. [2015] for instance) since, on the one hand, they tend to capture only short-term horizon signals, and on the other hand, such indicators would not be available for many banks in Europe that are not publicly listed. Their recursive logit model shows that CAMELS variables enter with the expected signs. Focusing on a panel of banks located in Middle East and North Africa countries, Calice [2014] also brings support to the efficiency of the set of CAMELS variables to predict banks' distress. With a different focus, DeYoung and Torna [2013] shows that asset-based non-traditional banking activities increased the probability of failure for US banks between 2008 and 2010.

Taking advantage of this rich existing literature, this paper will build on the standard EWS methodology to apply it to the case of the French banking system while taking into account its specificities.

3 Description of the dataset

3.1 A definition of banks' "distress" based on a supervisory rating

The bankruptcy of a bank is a very scarce event in France, fortunately for depositors and supervisors, but this scarcity of such extreme events is a major issue for researchers striving to predict them. In order to build an econometric model whose objective is to forecast banking "distress", we must first find a broader definition than pure bankruptcy.

In this paper, we rely on the output of a rating methodology that has been used between 1997 and 2013 by the French prudential and resolution authority, the *Autorité de contrôle prudentiel et de résolution* (ACPR), to score banks under its supervision.

This methodology takes into account all potential risks to which a bank can be exposed (credit quality of the portfolio, market risk, operational risk, concentration risk, etc.), as well as the quality of the management/governance, anti-money-laundering procedures, and so on. This scoring methodology does not imply mechanical formulas between some accounting ratios and the final score of a bank. Instead, supervisors use the entire quantitative and qualitative available information they have on the bank's situation to perform their assessment. This information comes from a variety of sources: the recurring quantitative prudential reporting to the ACPR as defined by the regulation, some internal documents of the banks that are sent to the supervisor, periodic interviews with the bank's senior management, on-site thematic inspections, etc.

At least once a year, each bank is scored according to this methodology and gets a rating on a five-notch scale from 1 to 5. Banks scored at 1 are considered to be in the "healthiest" situation: they have a very low risk profile and their management and risk mitigating process are very well adapted. On the contrary, banks scored at 5 require a particular attention from the supervisor due to their deteriorated situation. The cases of banks that score poorly are exposed to the ACPR Supervisory Board which can send formal requests to these banks to apply remedial actions (depending on the weaknesses revealed). If these banks which are explicitly required to take prompt corrective actions do not react to their main vulnerabilities identified by the supervisor, some sanctions can be imposed. Since this rating system has been at the core of the supervisory mechanism in France over the 1997-2013 period, it seems particularly relevant to use this information to base our definition of banking distress upon it.

The updating frequency of this rating by the supervisor varies across banks. Some banks can be scored several times per year, especially those with a high (bad) rating. In

77% of cases, there is only one score update per year, while there are two updates per year in 17% of cases, three updates in 4% of cases and four updates (or more) in 3% of cases. For this reason we chose to build our panel at *yearly* frequency, because using a quarterly frequency would generate a large number of spurious observations that would not be based on actual updates of the rating. And since our panel is at yearly frequency, for banks having several scores updates over the year, we will simply use the average of these scores over the year. The resulting unbalanced panel covers the period from 1997 to 2013 and includes a total of 5,042 observations based on 449 distinct banks. Figure 1 shows the distribution of the yearly average rating between 1997 and 2013. As one can notice, very few banks are rated 1, and around 60-80% of banks have a rating lower than or equal to 3.

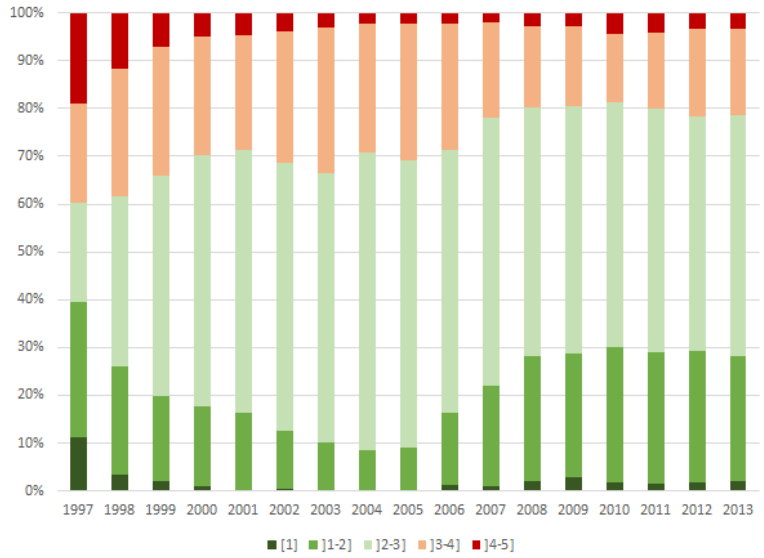

Figure 1: Distribution of banks rating over the years

Each time the situation of a bank is reassessed by the ACPR, either yearly or more frequently, its rating can remain the same, be improved or be downgraded. Table 1 displays the transition matrix of banks yearly average rating. We can notice that most of the banks keep a similar rating from one year to another, but this matrix also reveals

a significant number of downgrades (i.e. the rating increases from one year to another).

$N-1 \setminus N$	$[1]$	$]1-2]$	$]2-3]$	$]3-4]$	$]4-5]$
$[1]$	56.6%	38.3%	5.0%	0.0%	0.0%
$]1-2]$	2.4%	77.6%	18.9%	0.9%	0.0%
$]2-3]$	0.0%	6.9%	87.4%	5.2%	0.2%
$]3-4]$	0.0%	0.3%	15.2%	81.3%	2.9%
$]4-5]$	0.0%	0.0%	1.6%	25.5%	72.8%

Each row of this matrix adds up to 100%. Each cell gives the probability for a bank to get a given rating at the end of year N given its previous end-year rating.

Table 1: Banks' rating transition probability matrix

For the purpose of this paper, we will pay a particular attention to these downgrade situations, as we will identify "distressed" banks as those for which *a downgrade to rating 4 or 5 occurs* ***during*** *the year*. Using this definition of bank's distress, we identify 224 situations of distress out of the total 5,042 observations in our panel. Then, these "distressed" observations only represent 4.4% of our dataset. Note that, since some entities are assessed several times per year, an entity can start the year with a rating 3, be downgraded to 4 during the year and upgraded to 3 before the end of the year. In such case, the bank will be classified as "distressed" according to our definition. Note also that a given bank can be classified as distressed several times over the time-span of the panel. For this reason, the 224 distressed situations actually concern 163 distinct banks. As shown in table 2, among these 163 banks, 114 banks face a single distressed situation as long as they appear in our panel. 39 banks face two distress events, eight banks show three episodes of distress and only two banks face four distressed situations. These distress events affect all types of banks: private, state-owned and cooperative banks. Figure 2 illustrates the distribution of these 224 distressed observations over time.

Number of distinct banks having		Total distress events	*of which distinct banks by type:*		
			Private	*State-owned*	*Cooperative*
- 1 distress event:	114	114	*67*	*10*	*37*
- 2 distress events:	39	78	*19*	*6*	*14*
- 3 distress events:	8	24	*7*	*0*	*1*
- 4 distress events:	2	8	*2*	*0*	*0*
Total	163	224	*95*	*16*	*52*

Table 2: Distinct distressed banks and number of distress events

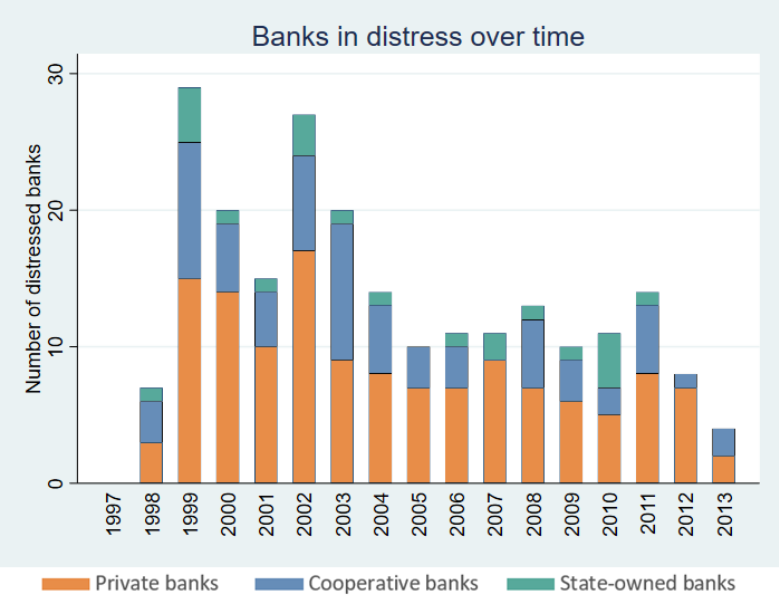

Figure 2: Evolution of number of distressed banks over time

3.2 A set of CAMELS and other bank-specific explanatory variables

Besides these crucial banks' ratings, we collected characteristics of these banks located in France that are under the scope of supervision of the ACPR. Building on the existing literature on early warning systems, we gathered a set of explanatory variables that could be classified into six main categories. As exposed above, such approach is often referred to as *CAMELS*, each letter standing for one of the six categories: *C*apital adequacy, *A*sset quality, *M*anagement, *E*arning ability, *L*iquidity and *S*ensitivity to market risk. We describe below these categories, their underlying variables and their expected effect on the probability of distress for banks. In order to avoid the influence of extreme outlier values, some of the explanatory variables displayed in this section have been

winsorized[1]. Finally, all variables used in this paper were constructed only on data from balance sheets, income statements and prudential reporting. No market-based data were used because, like in Betz et al. [2014], this would lead to exclude *de facto* most of French banks that are not publicly listed companies. For each entity in the panel, we use its data at the highest available level of consolidation.

Capital adequacy variables

Our first category of variable comprises two key prudential ratios: the total own funds (risk-weighted) solvency ratio, and the Basel III leverage ratio. The former is the most usual and traditional capital adequacy ratio used by banking supervisors. It divides total own funds of the bank by its total "risk-weighted assets" (RWA), which is a weighted measure of all the exposures of the banks, more or less weighted depending on their risk category. The latter is a new regulatory ratio that has been introduced in 2010 into the Basel III framework in order to refrain the build-up of excessive leverage in the banking system (BCBS 189 [2010]). It divides the Tier 1 capital by a total exposure measure composed by the total of all assets (with a particular treatment for derivatives and securities financing transactions) and by weighted amounts of some off-balance sheet items (financing commitments and guarantees granted). The exact computation of this ratio is obviously not possible over the entire period covered by our dataset since it only started to be monitored for some large banks starting from 2011. Instead, here we apply the best available proxy for this ratio: we divide the Tier 1 capital by the sum of total assets and some off-balance sheet items. Such construction of the Basel III leverage ratio proxy, based on supervisory data reported to the ACPR, ensures a closer measure to the real ratio than the rougher equity-to-asset ratio commonly used in the literature.

Better capitalised banks are supposed to be more protected against shocks and less likely to face a distress situation, as their higher amount of own funds enables to absorb

[1]This implies that for these variables, all observations larger (resp. lower) than the 99^{th} percentile (resp. the 1^{st} percentile) have been capped to the value observed at this 99^{th} (resp. 1^{st}) percentile.

larger losses. Higher capital adequacy ratios should therefore decrease the probability of entering into a distressed situation.

Asset quality variables

Banks investing in high quality assets should expect less losses than others. The share of non-performing loans (NPL) among the total loan portfolio is an indicator of the average asset quality of the banks. A higher amount of NPL should at some point translate into losses and increase banks' risk of facing a distress situation. Another indicator sometimes used in this category is the provisioning ratio of these NPL which divides the provisions over total assets. A bank that constitutes provisions for NPL should be seen as more careful, as it already anticipates future losses and builds provisions to help mitigating future turmoil. Therefore the higher this ratio, the lower should be the future probability of failure. On the other hand, this also reveals a generally poor quality of assets, which then induce a higher probability of failure. Hence the overall expected effect of this indicator is not so straightforward.

Management variables

A general argument found in the literature claims that better managed banks are less likely to fail and that a proxy of this management quality is the overhead costs over the operating income. If this is true, the lower this cost-efficiency ratio, the better the bank is managed and the lower should be its probability of facing a distress situation. Similarly, we can restrict this indicator to personnel expenses (still scaled by operating income).

Earning ability variables

Banks making profits are able to retain a fraction of earnings to build new own funds. In case of foreseen trouble, a profitable bank is therefore more able to avoid failure

since it can reduce the fraction of profit distributed in dividends to shareholders and use it to increase its own funds. A first indicator of profitability is the ratio of net operating income over total assets. A similar metric is the return on assets (ROA) which divides the net profit after taxes by total assets. From a theoretical perspective, on the one hand, the higher these ratios, the more profitable the bank is and the lower should be its probability of distress as it is more able to build new capital. But one the other hand, high profitability ratios can also be the sign of risky (high yield) assets and identify weak banks. Therefore the expected impact of these profitability ratios can go both ways. Moreover, we can expect a large volatility of the return on assets (ROA) to be a sign of trouble, as it indicates unstable earnings. Therefore we also include in this category the rolling standard deviation of the ROA (i.e. each year, the standard deviation of this metric is recomputed using all available past ROA values).

Liquidity variables

Deposits are supposed to be a relatively stable source of funding (compared to the issuance of bonds that need to be regularly renewed). Since long-term investments should be funded using stable sources, loans should generally be financed by deposits rather than by market funding. Therefore the loan to deposit ratio measures to which extent a bank uses collected deposits to finance its granted loans. The higher the ratio, the less loans are financed by deposits, the higher should be the probability of distress in case of a liquidity shock on the market. In this category we also include a proxy of the Basel III "Net Stable Funding Ratio" (hereafter "NSFR") which divides an "available stable funding" (ASF) measure by a "required stable funding" (RSF) measure. The ASF (resp. RSF) is a liquidity-weighted total liabilities (resp. assets) with larger weights put on more stable liability (resp. less liquid asset) categories. The higher the NSFR ratio, the more illiquid assets are funded with long-term stable liabilities, which should hedge a bank against maturity transformation risk and reduce its likelihood to face a distressed

situation.

Sensitivity to market risk variables

The sixth and last CAMELS category is the sensitivity to market risk, since the relative instability of this activity can lead to a distressed situation in case of a financial markets turmoil. We measure the exposure of a bank to market risk by the share of "market RWA" over total RWA. We also use the share of assets that are held for trading (HFTA) into total assets to capture this market risk dimension. The higher these ratios, the larger is the exposure to market risk and the higher should be the probability of distress.

Besides these six CAMELS categories, we include a set of additional control variables, such as the size of the bank, some business model characteristics, inter-bank liquidity variables and a measure of market power.

Size

Due to the well-know "too-big-to-fail" effect, large banks could be less likely to face a distressed situation. Then we include a size measure of banks using the logarithm of total assets, as it is often seen in the literature.

Business model variables

We also include some business model characteristics, such as the relative importance of granting loans in the activity of a bank (net loans to total assets), or investing in securities (securities held to total assets). We also capture the relative importance of collecting deposits (deposits to total assets) and issuing securities to fund the bank (securities issued to total assets). These variables will enable the model to control for the main business model orientations of the banks, either retail-oriented activities (collecting deposits and issuing loans), or oriented towards less traditional banking activities. We

also add the annual growth rate of credit in order to capture the influence of potential excessive past credit growth.

Inter-bank liquidity variables

We add two measures of inter-bank liquidity that captures the link of a given bank with the rest of the banking system: inter-bank assets (IBA), which are loans granted to other banks, and inter-bank liabilities (IBL), which are loans received from other banks. These two variables are scaled by total assets. If a bank mainly relies on the inter-bank market for funding, it is very sensitive to liquidity shocks in this market. Larger IBL should therefore increase the probability of distress. Conversely, banks having extra cash can lend it to other banks, usually through "reverse-repo" transactions with very short-term maturities. Therefore if they face a distress situation they can promptly benefit from this cash as those short-term operations mature and use it to restructure their balance sheet. Larger IBA should therefore decrease the probability of distress. Such inter-bank liquidity variables appeared to be key components of the BCBS methodology to assess the systemic impact of banks and identify "globally systemic important banks" (BCBS 255 [2013]), which motivates their inclusion in our set of control variables.

Market power

Finally, we want to take into account the effect of competition into our regressions. For this purpose, we compute a "Lerner index" for each bank at yearly frequency in order to get a measure of their market power, like in Fungàcovà and Weill [2013] and Maghyereh and Awartani [2014]. Appendix 4 provides the details of the computation of this Lerner index. A bank with a high market power (i.e. a large Lerner index) is expected to be able to extract more margin and profits, and therefore it should decrease its probability of distress.

Against this theoretical background, table 3 indicates for each variable its code used in the following regression tables and its expected sign in the results. Table 4 provides some summary statistics for all these explanatory and control variables, both for distressed and non-distressed banks, while table 5 shows these same statistics but using a breakdown by classes of supervisory rating.

Appendix 1 shows the correlation matrix between all these variables. Aside from a few cases showing relatively high correlation levels, most bivariate correlations remain moderate. Hence it seems that overall we do not face major collinearity issues. However, in order to deal with this potential collinearity issue, we will apply a stepwise approach on some regressions or split the set of CAMELS variables. Also, for each of these variables, appendix 2 provides the box plots of their lag for distressed and non distressed banks, while appendix 3 illustrates the evolution of each of these variables before and after the distress situation occurs.

CAMELS	Variable code	Variable name	Expected sign in regressions
C	TOW Solv Ratio	Total own funds solvency ratio	-
	LR B3	Basel III leverage ratio	-
A	Share NPL	Share of non performing loans	+
	PROV to TA	Provisioning ratio	+/-
M	Cost Eff	Cost efficiency	+
	Pers Exp	Personnel expenses	+
E	PROF	Profitability	+/-
	ROA	Return on assets	+/-
	Volatility of ROA	Rolling std. dev. of ROA	+
L	LOAN to DEP	Loan to deposit ratio	+
	NSFR	Proxy of the NSFR	-
S	Share MRK RWA	Share of market risk RWA	+
	HFTA to TA	Held for trading assets to total assets	+
Ctrl	SIZE	Size (logarithm of total assets)	-
	Net LOANS to TA	Net loans to total assets	+/-
	Credit Growth	Growth rate of credit	+
	SEC HELD to TA	Securities held to total assets	+/-
	DEP to TA	Deposits to total assets	+/-
	SEC ISSUED to TA	Securities issued to total assets	+/-
	IBA to TA	Inter-bank assets to total assets	-
	IBL to TA	Inter-bank liabilities to total assets	+
	Lerner Index	Lerner index	-

The sign +/- indicates that theoretical considerations are unclear about the expected sign.

Table 3: Expected signs of variables in the regressions

CAMELS	Variable	Mean *(std. dev.)*				Median		
		Non-distr.	Distr.	Stud. t		Non-distr.	Distr.	p-value
C	LR B3 (lag)	0.146 *(0.182)*	0.151 *(0.186)*	-0.439		0.077	0.076	0.986
	TOW Solv ratio (lag)	0.330 *(0.577)*	0.317 *(0.511)*	0.332		0.147	0.152	0.986
A	Share NPL (lag)	0.038 *(0.110)*	0.049 *(0.123)*	-1.420		0.011	0.014	0.099
	PROV to TA (lag)	0.018 *(0.049)*	0.022 *(0.055)*	-1.260		0.005	0.005	0.554
M	Cost Eff (lag)	0.443 *(0.483)*	0.588 *(0.729)*	-4.273	***	0.339	0.387	0.005
	Pers Exp (lag)	0.216 *(0.190)*	0.271 *(0.265)*	-4.198	***	0.185	0.214	0.005
E	ROA (lag)	0.009 *(0.026)*	-0.00 *(0.035)*	5.371	***	0.006	0.003	0.000
	STD ROA (lag)	0.009 *(0.018)*	0.015 *(0.025)*	-4.523	***	0.002	0.004	0.000
	PROF (lag)	0.060 *(0.101)*	0.055 *(0.059)*	0.643		0.035	0.036	0.637
L	NSFR (lag)	2.129 *(2.435)*	2.381 *(2.469)*	-1.510		1.046	1.271	0.000
	LOAN to DEP (lag)	6.284 *(15.90)*	5.119 *(13.27)*	1.078		1.070	0.795	0.033
S	Share MRK RWA (lag)	0.032 *(0.109)*	0.039 *(0.113)*	-1.016		0.000	0.000	0.749
	HFTA to TA (lag)	0.013 *(0.054)*	0.016 *(0.055)*	-0.993		0.000	0.000	0.006
Ctrl	SIZE (lag)	13.52 *(2.836)*	12.70 *(2.744)*	4.207	***	13.74	12.42	0.000
	Net LOANS to TA (lag)	0.481 *(0.331)*	0.402 *(0.311)*	3.499	***	0.514	0.377	0.001
	Credit Growth (lag)	0.048 *(0.425)*	-0.00 *(0.482)*	1.803	*	0.055	0.009	0.002
	SEC ISSUED to TA (lag)	0.062 *(0.148)*	0.045 *(0.123)*	1.704	*	0.000	0.000	0.002
	SEC HELD to TA (lag)	0.143 *(0.220)*	0.156 *(0.229)*	-0.846		0.058	0.053	0.827
	Lerner Index (lag)	0.483 *(0.186)*	0.492 *(0.237)*	-0.718		0.468	0.468	0.222
	DEP to TA (lag)	0.337 *(0.289)*	0.343 *(0.301)*	-0.318		0.280	0.305	0.787
	IBL to TA (lag)	0.264 *(0.261)*	0.261 *(0.272)*	0.159		0.179	0.164	0.749
	IBA to TA (lag)	0.229 *(0.240)*	0.230 *(0.236)*	-0.075		0.135	0.141	0.797

Statistics based on our yearly panel of 449 distinct banks from 1997 to 2013 with 224 distress events. For each CAMELS category and controls, variables are sorted by decreasing absolute value of Student's t. Statistical differences in medians are derived from the Kruskal-Wallis H test. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: Summary statistics by distress status

CAMELS	Variable	Score class [1-2]		[1-2] vs.]2-3]		Score class]2-3]		]2-3] vs.]3-5]		Score class]3-5]	
		Mean	Med.	Stud. t		Mean	Med.	Stud. t		Mean	Med.
C	TOW Solv ratio (lag)	0.448	0.149	5.789	***	0.312	0.145	2.242	**	0.277	0.151
	LR B3 (lag)	0.154	0.075	0.942		0.148	0.078	1.868	*	0.137	0.075
A	Share NPL (lag)	0.036	0.009	0.832		0.033	0.010	-5.651	***	0.052	0.019
	PROV to TA (lag)	0.012	0.004	-4.068	***	0.019	0.005	-1.553		0.022	0.005
M	Pers Exp (lag)	0.174	0.159	-4.743	***	0.204	0.185	-11.18	***	0.278	0.228
	Cost Eff (lag)	0.352	0.282	-4.679	***	0.430	0.338	-7.656	***	0.560	0.418
E	ROA (lag)	0.014	0.008	5.428	***	0.010	0.006	10.18	***	0.001	0.003
	STD ROA (lag)	0.008	0.002	-0.380		0.009	0.002	-4.438	***	0.011	0.003
	PROF (lag)	0.069	0.034	2.299	**	0.060	0.036	2.617	***	0.052	0.036
L	LOAN to DEP (lag)	5.946	1.199	-1.668	*	6.959	1.150	3.625	***	5.053	0.847
	NSFR (lag)	2.190	0.933	0.904		2.108	1.021	-0.727		2.166	1.209
S	HFTA to TA (lag)	0.013	0.000	-0.358		0.014	0.000	2.266	**	0.010	0.000
	Share MRK RWA (lag)	0.037	0.000	1.750	*	0.030	0.000	-0.596		0.032	0.000
Ctrl	SIZE (lag)	14.49	15.34	8.818	***	13.55	14.00	10.39	***	12.61	12.54
	Net LOANS to TA (lag)	0.504	0.628	0.336		0.500	0.568	8.123	***	0.413	0.387
	IBA to TA (lag)	0.221	0.116	1.083		0.211	0.124	-7.493	***	0.269	0.190
	Lerner Index (lag)	0.485	0.468	-1.697	*	0.496	0.468	5.785	***	0.459	0.468
	DEP to TA (lag)	0.303	0.262	-2.609	***	0.330	0.268	-4.806	***	0.377	0.358
	SEC ISSUED to TA (lag)	0.083	0.005	3.508	***	0.063	0.000	4.440	***	0.043	0.000
	Credit Growth (lag)	0.083	0.061	2.060	**	0.050	0.061	2.618	***	0.011	0.028
	IBL to TA (lag)	0.301	0.237	4.137	***	0.260	0.176	1.951	*	0.244	0.161
	SEC HELD to TA (lag)	0.154	0.082	1.040		0.145	0.054	1.490		0.134	0.038

Statistics based on our yearly panel of 449 distinct banks from 1997 to 2013. For each CAMELS category and controls, variables are sorted by decreasing absolute value of Student's t comparing means of classes]2-3] and]3-5]. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Summary statistics by supervisory rating classes

4 Estimating banks' probability of distress

4.1 Multivariate logit model

In order to model the probability of distress of the banks in our sample and then estimate the relative contributions of our explanatory variables, we use a multivariate logit model. We define D_{it} the binary variable which equals 1 if bank i is considered as distressed at time t, as defined in section 3.1 and 0 otherwise. Then we model the probability that a given bank i fails at time t using the vector X_i of observed explanatory CAMELS variables, the set BC_i of other bank-specific control variables, and a set of macroeconomic control variables M that includes short and long term interest rates, inflation, unemployment, GDP growth and a "crisis" time dummy variable (taking value 1 in 2007 and 2008). As an alternative to these macroeconomic variables, some time fixed effects (TFE_t) will also be tested in some regressions. In order to avoid potential endogeneity issues due to simultaneity of the regressors with the dependent variable, the three sets of variables X_i, BC_i and M are all lagged by one period (i.e. by one year). Therefore the estimated equation can be expressed as follows:

$$Pr(D_{i,t} = 1) = F(\alpha + \beta_1 \cdot X_{i,t-1} + \beta_2 \cdot BC_{i,t-1} + \beta_3 \cdot M_{t-1} + TFE_t + u_{i,t}) \quad (1)$$

where $F(.)$ is the logistic distribution and $u_{i,t}$ an error term.

Therefore, we try to determine to which extent a given indicator at time $t-1$ can be a predictor of distress at time t. Since we cannot be sure that observations are i.i.d. among banks, we clustered robust standard errors at bank level in all our following regressions.

4.2 Econometric results

Using the logistic model described above, we regress our binary "distress" variable on the set of CAMELS explanatory variables and additional control variables described in section 3. As explained before, all these explanatory and control variables are lagged by

one year in order to avoid potential endogeneity issues due to simultaneity between the distress indicator and the regressors.

Table 6 displays these logit regression results for seven alternative regressions, all based on equation (1). In regression (1), we apply a "horse-race" and regress our distress variable on the full set of lagged CAMELS and bank-specific control variables. In regressions (2) and (3), in order to avoid potential collinearity between these variables (for instance between the two capital adequacy ratios), we split each CAMELS category in halves and regress our dependent variable separately on these two subsets of CAMELS variables. Alternatively, still to avoid potential collinearity issues, regression (4) applies an iterative "stepwise" regression process[2] which reduces the number of regressors to the most relevant ones. Time fixed effects are included in the horse-race regression (5), while regression (6) includes our set of macroeconomic variables. Finally, regression (7) applies a stepwise regression on the full set of CAMELS, bank-specific controls and macroeconomic variables. Note that at this stage, since we apply logit regressions, the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can.

Our first variables of interest are the two capital adequacy ratios: the total own funds solvency ratio and the Basel III leverage ratio. Both ratios show the expected negative sign in all of the seven regressions, but only the leverage ratio is slightly significant in some regressions. This result appears surprising because better capitalized banks were supposed to be less likely to encounter a distressed situation. However, this may be an application of "Goodhart's law" which states that when an indicator becomes a

[2]In this iterative stepwise process, explanatory variables enter successively into the regression. The process starts with a simple univariate regression using as single regressor the explanatory variable most correlated with the dependent variable. Then the residuals of this first regression are computed. The next regressions add one by one as regressors the remaining explanatory variables that are most correlated with the previous regression's residuals. The process continues until no additional variable significant at a given level can be added to the regression. We set this level at 10% for all our stepwise regressions in this paper.

	Dependent variable: DISTRESS						
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TOW Solv ratio (lag)	-0.177	-0.005			-0.192	-0.164	
	(0.208)	(0.158)			(0.206)	(0.208)	
LR B3 (lag)	-0.481		-0.370	-1.068**	-0.345	-0.374	-0.939*
	(0.707)		(0.544)	(0.514)	(0.708)	(0.699)	(0.508)
Share NPL (lag)	0.197	0.352			0.384	0.432	
	(0.644)	(0.547)			(0.685)	(0.691)	
PROV to TA (lag)	-2.647		-2.405	-3.978**	-2.527	-2.586	-3.833*
	(2.218)		(2.206)	(2.013)	(2.161)	(2.197)	(1.976)
Cosf Eff (lag)	-0.023	0.445***			-0.068	-0.073	
	(0.177)	(0.132)			(0.190)	(0.188)	
Pers Exp (lag)	0.564		0.645		0.841	0.831	
	(0.509)		(0.450)		(0.534)	(0.529)	
PROF (lag)	-1.542	-0.815			-2.004*	-1.772*	
	(0.941)	(0.865)			(1.073)	(1.023)	
ROA (lag)	-8.935***		-12.775***	-12.518***	-8.387**	-8.143**	-12.029***
	(3.317)		(3.196)	(3.003)	(3.527)	(3.250)	(2.940)
Volatility of ROA (lag)	14.177***		13.697***	11.354***	15.538***	15.394***	12.027***
	(4.094)		(3.547)	(3.468)	(4.075)	(4.085)	(3.435)
LOAN to DEP (lag)	0.005	0.003			0.004	0.005	
	(0.005)	(0.005)			(0.005)	(0.005)	
NSFR (lag)	-0.118		0.088**	-0.159**	-0.116	-0.113	-0.151**
	(0.077)		(0.039)	(0.076)	(0.079)	(0.078)	(0.076)
Share MRK RWA (lag)	-0.001	0.712			0.398	0.198	
	(0.766)	(0.609)			(0.786)	(0.779)	
HFTA to TA (lag)	2.486**		1.170	1.752	2.415**	2.464**	1.818
	(1.214)		(1.153)	(1.115)	(1.222)	(1.239)	(1.130)
SIZE (lag)	-0.222***			-0.202***	-0.199***	-0.202***	-0.187***
	(0.043)			(0.040)	(0.043)	(0.044)	(0.040)
Net LOANS to TA (lag)	-1.925***			-1.632***	-1.901***	-1.868***	-1.568***
	(0.505)			(0.455)	(0.529)	(0.522)	(0.462)
Credit Growth (lag)	0.086				0.076	0.083	
	(0.195)				(0.189)	(0.195)	
SEC HELD to TA (lag)	-0.126				-0.191	-0.094	
	(0.508)				(0.531)	(0.522)	
DEP to TA (lag)	1.031*				1.023*	1.059*	
	(0.572)				(0.573)	(0.570)	
SEC ISSUED to TA (lag)	0.950				0.970	1.013	
	(0.870)				(0.852)	(0.860)	
IBA to TA (lag)	-1.497***			-1.202***	-1.493***	-1.475***	-1.187***
	(0.484)			(0.431)	(0.507)	(0.501)	(0.438)
IBL to TA (lag)	0.704				0.766	0.807	
	(0.617)				(0.610)	(0.611)	
Lerner Index (lag)	-0.480				-0.233	-0.249	
	(0.502)				(0.550)	(0.539)	
Crisis						0.322	
						(0.431)	
ST Interest Rate (lag)						0.087	0.105*
						(0.093)	(0.056)
LT Interest Rate (lag)						0.168	
						(0.173)	
Inflation (lag)						0.027	
						(0.237)	
Unemployment (lag)						0.325*	0.204***
						(0.178)	(0.067)
GDP growth (lag)						-14.368	
						(9.946)	
Intercept	1.093	-3.174***	-3.221***	1.262*	-0.181	-3.245	-1.221
	(0.930)	(0.125)	(0.148)	(0.713)	(1.042)	(2.469)	(1.043)
Bank-year observations	3,925	3,925	3,925	3,925	3,925	3,925	3,925
Area under ROC curve	0.6925	0.5646	0.6295	0.6837	0.7255	0.7032	0.6906
Horse-race regression	YES	NO	NO	NO	YES	YES	NO
Split CAMELS	NO	YES	YES	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	YES	NO	NO	YES
Time fixed effects	NO	NO	NO	NO	YES	NO	NO
Macro variables	NO	NO	NO	NO	NO	YES	YES

Note: Logistic regressions with robust standard errors clustered at bank level. This table shows the results of logit regressions, then the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks with an average number of 8.7 time periods per bank, leading to 3,925 bank-year observations. Regressions can either be "horse-race" (i.e. based on a full set of variables), or restricted to half of the set of explanatory variables ("split CAMELS"), or even based on a stepwise approach. For a detailed description of this stepwise approach, see footnote 2 in subsection 4.2. Main regressors are the set of CAMELS variables complemented by bank-specific control variables, as described in subsection 3.2. See table 3 for the matching between variable codes used in this table and their full names. Time fixed effects or a set of macroeconomic time-varying control variables are added in some regressions. Appendix 5 provides details about regression (7): it gives the order of variables in the stepwise iteration and their incremental contributions to the model efficiency.

Table 6: Multivariate logit regressions

policy target, it ceases to be a good predictive measure (Goodhart [1981]). In our case, since capital adequacy ratios are at the core of prudential supervision and are the most monitored indicators by supervisors, market participants and banks themselves, it is then not so surprising that they lost their predictive power in such an EWS model.

***Result n^o 1**: Capital adequacy ratios do not appear as very efficient predictors of banks' distress, which might be an application of "Goodhart's law".*

Regarding the asset quality variables (share of NPL and provisioning ratio), only the latter seems to be significant in some regressions. This implies that the more non-performing loans are provisioned, the less likely the bank will face a distressed situation. As for the main management variable (cost efficiency), it is statistically significant only in one regression with its expected positive sign. On the contrary, the personnel expenses variable does not appear significant.

Among earning ability variables (profitability and return on assets), the ROA appears to be a very significant predictor of distress: the sign is negative in each regression and the level of significance is high (p-value lower to 5% for all our regressions). The profitability variable (net operating income over total assets) only appears as slightly significant in some regressions, presumably because it is positively correlated with the ROA which captures most of the significativity. We also notice a very high level of significance for the volatility of the ROA (measured as its rolling standard deviation at bank level), with a positive sign. This highlights that the higher the volatility of banks' earnings, the higher their probability of distress. Overall, these regressions bring strong support to this "earning ability" dimension of the set of CAMELS variables in the context of the French banking sector.

The liquidity variable loan-to-deposit ratio does not appear significant in any regression, while our proxy of the Basel III net stable funding ratio (NSFR) sometimes seems significant, generally with a negative sign. Therefore the higher the NSFR (i.e. the

more long-term assets are financed by long-term resources), the lower the probability of distress. As for the sensitivity to market risk variables, the ratio of held-for-trading assets in total assets shows the expected positive significant sign in most regressions.

Result n°2: *Our regression results bring general support to the usual set of CAMELS variables in an early warning system for the French banking sector, and the main determinants of distress appear to be the profitability of banks' assets, measured by the ROA, and its volatility.*

Looking at the set of bank-specific control variables that we included besides the CAMELS, we first notice that the size of the bank shows a very high significance level with a negative sign in all regressions. This means that, everything else equal, larger banks are less likely to face a distress situation. Such finding may come from the fact that largest banks receive more attention from the supervisor (notably because of their "too-big-to-fail" status). Hence more pre-emptive actions might be taken by the supervisor for these banks, long before they face a distress situation.

We also find strong support for one of our two inter-bank liquidity variables we introduced into the regressions (ratio of inter-bank assets and inter-bank liabilities to total assets). The inter-bank assets ratio displays its expected negative sign with very large level of significance. This result brings support to the inter-bank liquidity rationale described in previous section: banks lending extra cash to other banks, usually in very short maturity operations, can stop renewing such inter-bank lending and use this cash to restructure the balance sheet if they face a distress situation. So larger inter-bank assets decreases the probability of distress.

Finally, we find no empirical support for an impact of market power of banks on their likeliness to face a distress situation, since the Lerner Index does not enter significantly in any regression. However, it shows the expected negative sign in all regressions.

In table 7 we compute the marginal effects of all significant variables in our seven regressions displayed in table 6. The variable return on assets (ROA), and its volatility,

Result n°3: *Besides usual CAMELS variables, taking into account the size and inter-bank liquidity of banks seems relevant in the case of an early warning system for the French banks.*

have the largest marginal effects. Looking at regression (7), they are respectively estimated at -0.55 and +0.55 This implies that everything else equal, increasing the ROA of a bank at time t by one basis point (i.e. moving for instance from 0.40% to 0.41%), or reducing its volatility by one basis point, should both reduce its probability of distress at time $t+1$ by approximately 0.55%.

	Marginal effects of each significant variable on probability of DISTRESS						
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LR B3 (lag)				-0.049**			-0.043*
				(0.024)			(0.023)
PROV to TA (lag)				-0.182*			-0.174*
				(0.093)			(0.091)
Cosf Eff (lag)		0.021***					
		(0.006)					
PROF (lag)					-0.090*	-0.080*	
					(0.049)	(0.047)	
ROA (lag)	-0.406***		-0.590***	-0.571***	-0.376**	-0.368**	-0.546***
	(0.152)		(0.153)	(0.140)	(0.158)	(0.147)	(0.136)
Volatility of ROA (lag)	0.645***		0.632***	0.518***	0.697***	0.696***	0.546***
	(0.188)		(0.166)	(0.158)	(0.184)	(0.186)	(0.157)
NSFR (lag)			0.004**	-0.007**			-0.007**
			(0.002)	(0.004)			(0.003)
HFTA to TA (lag)	0.113**			0.080	0.108**	0.111**	0.083
	(0.055)			(0.050)	(0.054)	(0.055)	(0.051)
SIZE (lag)	-0.010***			-0.009***	-0.009***	-0.009***	-0.008***
	(0.002)			(0.002)	(0.002)	(0.002)	(0.002)
Net LOANS to TA (lag)	-0.088***			-0.074***	-0.085***	-0.084***	-0.071***
	(0.024)			(0.022)	(0.025)	(0.025)	(0.022)
DEP to TA (lag)	0.047*				0.046*	0.048*	
	(0.026)				(0.026)	(0.026)	
IBA to TA (lag)	-0.068***			-0.055***	-0.067***	-0.067***	-0.054***
	(0.023)			(0.020)	(0.023)	(0.023)	(0.021)
ST Interest Rate (lag)							0.005*
							(0.003)
Unemployment (lag)						0.015*	0.009***
						(0.008)	(0.003)
Bank-year observations	3,925	3,925	3,925	3,925	3,925	3,925	3,925
Horse-race regression	YES	NO	NO	NO	YES	YES	NO
Split CAMELS	NO	YES	YES	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	YES	NO	NO	YES
Time fixed effects	NO	NO	NO	NO	YES	NO	NO
Macro variables	NO	NO	NO	NO	NO	YES	YES

Note: Marginal effects on the probability of distress of the significant variables of each of our seven regressions displayed in table 6. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks with an average number of 8.7 time periods per bank, leading to 3,925 bank-year observations. Marginal effects are computed around the average point.

Table 7: Multivariate logit marginal effects

4.3 Models' sensitivity and specificity for in-sample predictions

Like in any prediction model, we face two different issues. On the one hand, we do not want the model to miss (too many) true distress cases, but on the other hand, we

also want to minimise the number of false alarms. For a given probability cut-off, the *sensitivity* of the model is its ability to correctly predict real failures, and the *specificity* of the model is its ability to correctly predict non-failures.

Figure 3 displays, on the left hand side, the sensitivity and the specificity of our regression (7) described in table 6 for all cut-off probabilities between 0 and 1, and the ROC curve on the right hand side.

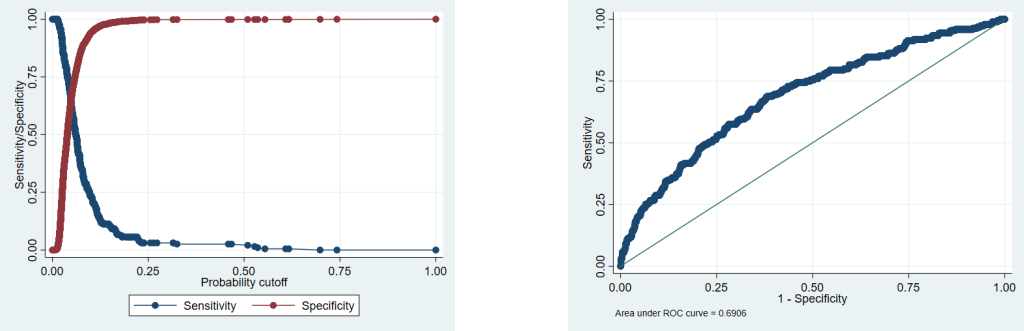

Figure 3: Regression (7) - Sensitivity and specificity levels (left) ; ROC curve (right)

In the spirit of Theodossiou et al. [1996], in order to determine the optimal probability cut-off p, we define a cost function of the following form:

$$\min_p Cost(p) = \alpha_0 + \alpha_1 \,.\, Sensitivity(p) + \alpha_2 \,.\, Specificity(p)$$

Setting α_0 to 1 and α_1 and α_2 to -1, we obtain the Youden index (cf. Youden [1950] and Candelon et al. [2012]) that puts equal weights on the sensitivity and the specificity. However, note that this equal weighting of type 1 and type 2 errors may not reflect the true preference of the ACPR. Therefore we try to maximize the following expression: $Sensitivity(p) + Specificity(p) - 1$. As showed in table 8, this leads to set the optimal cut-off probability to 5.50% . With this cut-off, we obtain a rather satisfying efficiency for our model. 71.0% of observations are correctly classified, the sensitivity equals 57.4% and the specificity reaches 71.7%. 112 out of 195 distress situations and 2,677 non-distress situations out of 3,730 are correctly predicted one year ahead, leading

to only 83 unpredicted distresses for 1,053 false alarms.

Moving to a 4.5% probability cut-off, for instance, would improve the sensitivity to 69.2%, which means that 135 out of 195 distress situations would pre-emptively be detected, leaving only 60 unforeseen distress situations. However, this comes at the cost of specificity which falls down to 59.8% since the model now triggers 1,496 false alarms.

Probability cut-off	Predicted Distress	Non-predicted Distress	False alarms	Predicted non-distress	Sensitivity	Specificity	Correctly classified obs.	Youden index
4.50%	135	60	1,496	2,234	69.2%	59.8%	60.3%	0.291
4.75%	128	67	1,363	2,367	65.6%	63.4%	63.5%	0.291
5.00%	121	74	1,244	2,486	62.0%	66.6%	66.4%	0.287
5.25%	115	80	1,147	2,583	58.9%	69.2%	68.7%	0.282
5.50%	**112**	**83**	**1,053**	**2,677**	**57.4%**	**71.7%**	**71.0%**	**0.292**
5.75%	104	91	967	2,763	53.3%	74.0%	73.0%	0.274
6.00%	99	96	891	2,839	50.7%	76.1%	74.8%	0.269
6.25%	96	99	822	2,908	49.2%	77.9%	76.5%	0.272
6.50%	88	107	750	2,980	45.1%	79.8%	78.1%	0.250
6.75%	82	113	684	3,046	42.0%	81.6%	79.6%	0.237
7.00%	81	114	615	3,115	41.5%	83.5%	81.4%	0.251

Note: Using lagged variables (in order to avoid potential endogeneity issues) mechanically reduces the number of available observations, compared to what was exposed in subsection 3.1 describing the distress variable. Moreover, for some banks, not all explanatory variables at time $t-1$ were always available to predict failure (or non-failure) at time t. Here 3,925 observations remain, of which 195 distress and 3,730 non-distress situations. The bold line indicates the probability cut-off that maximizes the Youden index (or Youden's J statistic), which is defined as $J = Sensitivity + Specificity - 1$.

Table 8: Model's efficiency for several probability cut-offs

***Result n°4**: The efficiency of our EWS model appears rather satisfying as it correctly classifies more than 70% of observations one year ahead.*

On the other hand, this level of efficiency of the model, as well as the area under ROC curve (displayed in table 6) close to 0.7, tend to show that accounting data used to build the set of CAMELS variables is not sufficient to fully explain the situation of banks, as seen by the supervisor. This indicates that besides quantitative metrics used in this paper to assess the situation of banks, there remain a discretionary dimension in the assessment made by the supervisor. Based on the deep knowledge of the banks and their activity, banking supervisors are able to factor in various other elements into the final rating that reflects the overall situation of the assessed bank. Fortunately for financial stability, banking supervisors still know more than an early warning system model.

4.4 Models' sensitivity and specificity for out-of-sample predictions

In order to supplement previous subsections that comment on *in-sample* efficiency of our model, this subsection presents its efficiency for *out-of-sample* predictions.

We start by randomly splitting our dataset into two unequal parts. We run our seven different econometric regressions (as exposed in table 6) using the first part of the dataset that contains 75% of our observations. Then we use these estimations to predict the distress status (in distress or not) of the remaining 25% observations, and compare the predicted result with the real status of banks. Like in previous subsections, it is possible to compute the share of real distress (resp. non-distress) situations correctly predicted one year ahead: the sensitivity (resp. specificity) of the model for out-of-sample predictions. As identified with in-sample predictions' efficiency, we use the optimal 5.5% probability cut-off for these out-of-sample predictions.

This procedure is repeated 100 times, each time with a new random split of the dataset. The sensitivity, the specificity, the percentage of correctly classified observations and the area under ROC curve of the seven models are finally averaged over these 100 random draws. Table 9 displays these averaged statistics for out-of-sample predictions.

	Regression						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Out-of-sample sensitivity	54.5%	22.1%	39.3%	54.1%	54.8%	56.4%	53.8%
Out-of-sample specificity	55.7%	75.8%	67.1%	57.8%	56.6%	55.9%	58.2%
Correctly classified obs.	55.6%	73.4%	65.9%	57.6%	56.5%	55.9%	58.0%
Area under ROC curve	0.699	0.567	0.634	0.677	0.735	0.711	0.684
Horse-race regression	YES	NO	NO	NO	YES	YES	NO
Split CAMELS	NO	YES	YES	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	YES	NO	NO	YES
Time fixed effects	NO	NO	NO	NO	YES	NO	NO
Macro variables	NO	NO	NO	NO	NO	YES	YES

Note: These measures for out-of-sample predictions are averages of the individual measures for each of the 100 estimations performed on random splits of the initial dataset. We use the 5.5% optimal probability cut-off derived from in-sample efficiency analysis. The columns correspond to the seven regressions shown in table 6.

Table 9: Out-of-sample efficiency

The out-of-sample sensitivity of our seventh regression reaches 54%. This means that our early warning system, once calibrated using one part of the dataset (three quarters

of all available observations), can - on average - correctly predict one year ahead a bit more than half of future distress situations of the remaining part of the dataset. As for the specificity, its average over the seven models reaches 61.1%, which implies that a bit less than two third of out-of-sample real non-distress situations are correctly predicted, which triggers a reasonable number of "false alarms".

***Result n°5**: Like for in-sample predictions, the out-of-sample efficiency of our model seems rather satisfying as around 60% of observations are correctly predicted.*

5 Regressions by type of bank

In order to take into account one key characteristic of the French banking sector, in this subsection we re-run some regressions splitting our dataset by type of bank. Indeed, looking at bank ownership, we can identify three main types of bank in France.

- Some of them are mainly owned (i.e. 50% or more of their capital is hold) by the state or a state-related entity. These banks will be considered as *"state-owned"* banks.

- The French law[3] officially defines three networks of *"cooperative"* banks: Group Crédit Agricole, Group Crédit Mutuel and Group Banques Populaires Caisses d'Epargne (BPCE). Each of these three networks is composed by many regional banks called *"caisses"*, and their owners are not traditional shareholders but individual depositors of these banks. The capital of these banks is not traded and listed on a stock market, it is held by these client-shareholders called "sociétaires". Each "caisses" of these three networks in our panel will be labelled as a "cooperative" bank.

[3] "Code monétaire et financier" article L511-30

- All other remaining banks owned by private shareholders will simply be considered as *"private"* banks.

Over the 449 distinct banks of our panel, 25 are state-owned banks, 233 are cooperative banks and 191 are private banks, according to the above definitions. In terms of distress events, among the total 224 distressed situations collected in the panel and described in subsection 3.1, 22 events relates to state-owned banks, 68 to cooperative banks and 134 to private banks. Considering that a given bank can face several distress events over time, as exposed in section 3.1, there is a total of 163 distinct banks that face at least one distress situation. Among them, there are 16 state-owned banks, 52 cooperative banks and 95 private banks (cf. table 2) that are considered as distress banks at least once over the full time-span of our panel.

Tables 10, 11 and 12 replicate table 4 for the three types of bank: private, state-owned and cooperative. Simply looking at the univariate mean-difference t-tests, we already see first indications that determinants may not always be the same across these three different types of bank. Appendix 1 shows the correlation matrices of all explanatory variables for each bank type.

In table 13 we re-run regressions (1) and (7) shown in table 6, but each time the dataset is restricted to one of these three types of bank. The purpose of this analysis is to assess whether the general ex-ante determinants of banks' distress identified in previous sections are homogeneous across these three types of bank, or if some banks have specific drivers of distress.

Regression (7) is based on a stepwise process that only selects the most significant variables, therefore we can explore for each type of bank whether their main drivers of distress are similar or not. It appears that it is actually not that much the case. Looking

CAMELS	Variable	Mean *(std. dev.)*				Median		
		Non-distr.	Distr.	Stud. t		Non-distr.	Distr.	p-value
C	LR B3 (lag)	0.185 *(0.196)*	0.165 *(0.186)*	1.103		0.104	0.085	0.318
	TOW Solv ratio (lag)	0.441 *(0.661)*	0.377 *(0.620)*	1.099		0.226	0.197	0.061
A	PROV to TA (lag)	0.025 *(0.067)*	0.029 *(0.067)*	-0.754		0.004	0.005	0.123
	Share NPL (lag)	0.045 *(0.125)*	0.050 *(0.129)*	-0.464		0.004	0.010	0.116
M	Pers Exp (lag)	0.230 *(0.243)*	0.293 *(0.306)*	-2.857	***	0.173	0.227	0.019
	Cost Eff (lag)	0.545 *(0.655)*	0.705 *(0.901)*	-2.673	***	0.397	0.415	0.178
E	ROA (lag)	0.012 *(0.038)*	-0.00 *(0.044)*	4.569	***	0.007	0.002	0.000
	STD ROA (lag)	0.015 *(0.022)*	0.021 *(0.030)*	-2.975	***	0.006	0.009	0.065
	PROF (lag)	0.085 *(0.142)*	0.067 *(0.070)*	1.468		0.040	0.039	0.886
L	LOAN to DEP (lag)	7.234 *(17.96)*	5.318 *(14.19)*	1.211		0.553	0.520	0.561
	NSFR (lag)	3.060 *(2.770)*	2.951 *(2.786)*	0.442		1.791	1.717	0.540
S	Share MRK RWA (lag)	0.054 *(0.154)*	0.049 *(0.138)*	0.388		0.000	0.000	0.783
	HFTA to TA (lag)	0.016 *(0.064)*	0.018 *(0.059)*	-0.224		0.000	0.000	0.484
Ctrl	IBL to TA (lag)	0.197 *(0.257)*	0.269 *(0.292)*	-3.116	***	0.067	0.151	0.003
	SEC ISSUED to TA (lag)	0.064 *(0.168)*	0.028 *(0.090)*	2.484	**	0.000	0.000	0.471
	IBA to TA (lag)	0.266 *(0.280)*	0.225 *(0.258)*	1.626		0.156	0.108	0.124
	SIZE (lag)	12.31 *(2.455)*	12.06 *(2.317)*	1.135		12.03	12.17	0.579
	Credit Growth (lag)	0.027 *(0.596)*	-0.02 *(0.592)*	0.867		0.021	-0.01	0.279
	Net LOANS to TA (lag)	0.314 *(0.315)*	0.329 *(0.317)*	-0.547		0.216	0.224	0.328
	DEP to TA (lag)	0.265 *(0.290)*	0.279 *(0.285)*	-0.537		0.146	0.183	0.395
	SEC HELD to TA (lag)	0.195 *(0.275)*	0.182 *(0.265)*	0.513		0.044	0.046	0.951
	Lerner Index (lag)	0.508 *(0.228)*	0.513 *(0.278)*	-0.284		0.468	0.519	0.264

Statistics based on our yearly panel of 191 distinct private banks from 1997 to 2013 with 134 distress events. For each CAMELS category and controls, variables are sorted by decreasing absolute value of Student's t. Statistical differences in medians are derived from the Kruskal-Wallis H test. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Summary statistics by distress status for private banks

CAMELS	Variable	Mean *(std. dev.)*				Median		
		Non-distr.	Distr.	Stud. t		Non-distr.	Distr.	p-value
C	TOW Solv ratio (lag)	0.497 *(0.481)*	0.459 *(0.403)*	0.361		0.390	0.342	0.876
	LR B3 (lag)	0.328 *(0.286)*	0.323 *(0.280)*	0.086		0.220	0.273	0.964
A	PROV to TA (lag)	0.022 *(0.038)*	0.010 *(0.022)*	1.477		0.004	0.002	0.158
	Share NPL (lag)	0.080 *(0.180)*	0.068 *(0.148)*	0.311		0.030	0.036	0.993
M	Pers Exp (lag)	0.335 *(0.199)*	0.398 *(0.223)*	-1.451		0.332	0.372	0.312
	Cost Eff (lag)	0.537 *(0.297)*	0.625 *(0.283)*	-1.358		0.531	0.569	0.320
E	ROA (lag)	0.011 *(0.020)*	0.005 *(0.015)*	1.318		0.006	0.004	0.025
	PROF (lag)	0.061 *(0.034)*	0.058 *(0.031)*	0.418		0.056	0.051	0.371
	STD ROA (lag)	0.011 *(0.018)*	0.010 *(0.013)*	0.163		0.005	0.006	0.857
L	NSFR (lag)	1.376 *(1.340)*	1.247 *(0.642)*	0.447		0.955	1.087	0.528
	LOAN to DEP (lag)	13.22 *(19.65)*	11.56 *(17.05)*	0.388		2.665	3.320	0.847
S	HFTA to TA (lag)	0.007 *(0.027)*	0.010 *(0.033)*	-0.519		0.000	0.000	0.787
	Share MRK RWA (lag)	0.007 *(0.030)*	0.007 *(0.017)*	0.011		0.000	0.000	0.352
Ctrl	SEC HELD to TA (lag)	0.069 *(0.120)*	0.107 *(0.180)*	-1.387		0.012	0.011	0.788
	Credit Growth (lag)	-0.00 *(0.315)*	-0.08 *(0.391)*	1.185		0.013	-0.03	0.058
	Lerner Index (lag)	0.522 *(0.185)*	0.551 *(0.091)*	-0.736		0.529	0.552	0.756
	SIZE (lag)	11.49 *(2.614)*	11.13 *(2.492)*	0.643		10.82	11.07	0.617
	DEP to TA (lag)	0.248 *(0.259)*	0.274 *(0.294)*	-0.459		0.134	0.142	0.611
	Net LOANS to TA (lag)	0.632 *(0.260)*	0.622 *(0.234)*	0.179		0.723	0.691	0.554
	IBL to TA (lag)	0.219 *(0.234)*	0.212 *(0.231)*	0.135		0.166	0.125	0.867
	SEC ISSUED to TA (lag)	0.053 *(0.147)*	0.057 *(0.179)*	-0.109		0.000	0.000	0.660
	IBA to TA (lag)	0.203 *(0.218)*	0.207 *(0.220)*	-0.092		0.129	0.128	0.844

Statistics based on our yearly panel of 25 distinct state-owned banks from 1997 to 2013 with 22 distress events. For each CAMELS category and controls, variables are sorted by decreasing absolute value of Student's t. Statistical differences in medians are derived from the Kruskal-Wallis H test. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 11: Summary statistics by distress status for state-owned banks

at results for private banks, we notice a strongly significant negative sign for the return on assets (ROA) and a positive sign for its volatility, which is not the case for state-owned and cooperative banks. This means that the general result on the impact of the ROA and its stability on the probability of distress that we obtained in this paper on the full panel is actually driven by private banks. This seems logical given the fact that,

CAMELS	Variable	Mean *(std. dev.)*				Median		
		Non-distr.	Distr.	Stud. t		Non-distr.	Distr.	p-value
C	LR B3 (lag)	0.080 *(0.094)*	0.067 *(0.063)*	1.110		0.063	0.049	0.003
	TOW Solv ratio (lag)	0.203 *(0.476)*	0.153 *(0.123)*	0.862		0.121	0.108	0.016
A	Share NPL (lag)	0.025 *(0.070)*	0.040 *(0.103)*	-1.729	*	0.012	0.013	0.282
	PROV to TA (lag)	0.011 *(0.026)*	0.012 *(0.028)*	-0.354		0.005	0.006	0.592
M	Pers Exp (lag)	0.183 *(0.109)*	0.188 *(0.135)*	-0.377		0.181	0.189	0.822
	Cost Eff (lag)	0.338 *(0.251)*	0.347 *(0.215)*	-0.320		0.314	0.326	0.452
E	ROA (lag)	0.006 *(0.008)*	0.002 *(0.008)*	3.215	***	0.005	0.003	0.000
	PROF (lag)	0.037 *(0.042)*	0.032 *(0.023)*	0.999		0.032	0.028	0.076
	STD ROA (lag)	0.003 *(0.009)*	0.003 *(0.005)*	0.237		0.001	0.001	0.203
L	LOAN to DEP (lag)	4.270 *(12.48)*	2.644 *(8.707)*	1.066		1.203	0.843	0.000
	NSFR (lag)	1.429 *(1.929)*	1.623 *(1.760)*	-0.821		0.821	1.081	0.000
S	Share MRK RWA (lag)	0.016 *(0.048)*	0.031 *(0.063)*	-2.465	**	0.000	0.000	0.358
	HFTA to TA (lag)	0.010 *(0.046)*	0.016 *(0.052)*	-0.963		0.000	0.000	0.063
Ctrl	Net LOANS to TA (lag)	0.603 *(0.288)*	0.473 *(0.272)*	3.682	***	0.718	0.500	0.000
	DEP to TA (lag)	0.416 *(0.271)*	0.492 *(0.284)*	-2.287	**	0.366	0.603	0.020
	IBL to TA (lag)	0.331 *(0.252)*	0.261 *(0.245)*	2.257	**	0.254	0.176	0.024
	IBA to TA (lag)	0.201 *(0.197)*	0.247 *(0.195)*	-1.923	*	0.129	0.223	0.020
	SIZE (lag)	14.93 *(2.459)*	14.48 *(2.762)*	1.495		15.48	15.03	0.034
	Lerner Index (lag)	0.454 *(0.133)*	0.431 *(0.156)*	1.421		0.468	0.418	0.013
	Credit Growth (lag)	0.075 *(0.224)*	0.050 *(0.120)*	0.835		0.069	0.066	0.426
	SEC ISSUED to TA (lag)	0.062 *(0.128)*	0.075 *(0.151)*	-0.832		0.008	0.006	0.884
	SEC HELD to TA (lag)	0.110 *(0.161)*	0.120 *(0.148)*	-0.516		0.066	0.083	0.289

Statistics based on our yearly panel of 233 distinct cooperative banks from 1997 to 2013 with 68 distress events. For each CAMELS category and controls, variables are sorted by decreasing absolute value of Student's t. Statistical differences in medians are derived from the Kruskal-Wallis H test. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 12: Summary statistics by distress status for cooperative banks

compared to state-owned and cooperative banks, private banks are expected to be more profit-oriented, leading supervisors to assess them as weaker and more prone to face a distressed situation when their ROA is too low and/or too volatile.

Private banks also appear strongly impacted by inter-bank liquidity variables. As seen in previous section, inter-bank assets constitute a reserve of liquid assets that can easily and promptly be converted into cash and therefore it provides a security buffer against shocks for banks having "extra-cash" to lend on the inter-bank market. On the other hand, relying on inter-bank liabilities to fund the balance sheet may become a source of vulnerability, and this is empirically well verified in the case of private banks.

As for cooperative banks, we notice that a larger share of assets held for trading appears to be a driver of distress, and simultaneously, a higher fraction of the balance sheet dedicated to the issuance of loans reduces the probability of distress. These two results bring support to the idea that, among cooperative banks, those that deviated more from the traditionnal loan-issuance activity to engage in market-oriented activities tended to face more distress events. Besides, the general result obtained on the full panel relative to the effect of banks' size on their probability of distress is actually driven by

	Dependent variable: DISTRESS							
Regression	(1)				(7)			
Bank type	All	Priv.	S.O.	Coop.	All	Priv.	S.O.	Coop.
TOW Solv ratio (lag)	-0.177	-0.102	-1.628**	-1.293				
	(0.208)	(0.269)	(0.784)	(1.549)				
LR B3 (lag)	-0.481	-0.456	-4.531	-0.760	-0.939*			
	(0.707)	(1.027)	(3.850)	(4.152)	(0.508)			
Share NPL (lag)	0.197	0.283	-20.872**	2.115				1.126
	(0.644)	(0.793)	(8.484)	(1.444)				(0.722)
PROV to TA (lag)	-2.647	-1.909	-53.561***	8.459	-3.833*		-21.43**	
	(2.218)	(2.153)	(12.78)	(6.004)	(1.976)		(9.521)	
Cosf Eff (lag)	-0.023	-0.019	8.618***	-3.151*			1.541**	
	(0.177)	(0.203)	(2.740)	(1.713)			(0.745)	
Pers Exp (lag)	0.564	0.583	-7.843*	4.253				
	(0.509)	(0.544)	(4.761)	(3.474)				
PROF (lag)	-1.542	-1.462	15.73	-1.543				
	(0.941)	(1.043)	(10.17)	(7.668)				
ROA (lag)	-8.935***	-9.129***	-48.33***	-13.057	-12.029***	-12.647***		
	(3.317)	(3.408)	(13.25)	(14.58)	(2.940)	(3.055)		
Volatility of ROA (lag)	14.177***	12.752***	6.623	33.679	12.027***	11.063***		
	(4.094)	(4.738)	(18.15)	(24.24)	(3.435)	(4.008)		
LOAN to DEP (lag)	0.005	-0.004	0.019	0.020				
	(0.005)	(0.007)	(0.024)	(0.017)				
NSFR (lag)	-0.118	-0.067	-2.467	0.094	-0.151**			
	(0.077)	(0.084)	(2.002)	(0.251)	(0.076)			
Share MRK RWA (lag)	-0.001	0.115	-6.657	-2.767				
	(0.766)	(0.779)	(9.528)	(3.058)				
HFTA to TA (lag)	2.486**	1.329	-5.080	9.871***	1.818			6.672***
	(1.214)	(1.625)	(6.474)	(2.458)	(1.130)			(1.674)
SIZE (lag)	-0.222***	-0.137**	0.015	-0.361***	-0.187***			-0.258***
	(0.043)	(0.066)	(0.279)	(0.095)	(0.040)			(0.063)
Net LOANS to TA (lag)	-1.925***	-0.949	-10.323**	-1.814	-1.568***			-1.868***
	(0.505)	(0.629)	(5.160)	(1.265)	(0.462)			(0.622)
Credit Growth (lag)	0.086	0.132	-0.881	0.254				
	(0.195)	(0.202)	(1.204)	(0.920)				
SEC HELD to TA (lag)	-0.126	-0.079	-5.799	-0.598				
	(0.508)	(0.586)	(4.668)	(1.393)				
DEP to TA (lag)	1.031*	0.173	-5.720**	5.107***				4.173***
	(0.572)	(0.610)	(2.477)	(1.145)				(0.932)
SEC ISSUED to TA (lag)	0.950	-1.078	-7.717	4.796***		-1.968**		5.103***
	(0.870)	(0.931)	(5.018)	(0.873)		(0.821)		(0.758)
IBA to TA (lag)	-1.497***	-1.369**	-11.453**	-1.045	-1.187***	-0.847**		
	(0.484)	(0.533)	(4.792)	(1.235)	(0.438)	(0.359)		
IBL to TA (lag)	0.704	1.180*	-9.583***	2.046		0.800**		2.199**
	(0.617)	(0.666)	(3.404)	(1.343)		(0.371)		(0.925)
Lerner Index (lag)	-0.480	-0.083	-1.688	-3.701**				
	(0.502)	(0.570)	(3.306)	(1.490)				
Intercept	1.093	-0.277	14.998**	1.408	-1.221	-2.524***	-1.828***	-3.938***
	(0.930)	(1.243)	(5.987)	(2.076)	(1.043)	(0.209)	(0.659)	(1.512)
Bank-year observations	3,925	1,630	377	1,918	3,925	1,630	377	1,918
Number of distinct banks	449	191	25	233	449	191	25	233
Average periods per bank	8.7	8.5	15.1	8.2	8.7	8.5	15.1	8.2
Area under ROC curve	0.6925	0.6909	0.8028	0.7628	0.6906	0.6693	0.7707	0.7405
Horse-race regression	YES	YES	YES	YES	NO	NO	NO	NO
Split CAMELS	NO	NO	NO	NO	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	NO	YES	YES	YES	YES
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO
Macro variables	NO	NO	NO	NO	YES	YES	YES	YES

Note: Logistic regressions with robust standard errors clustered at bank level. This table shows the results of logit regressions, then the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks, of which 25 "state-owned" banks (S.O.), 233 "cooperative" banks (Coop.) and 191 "private" banks (Priv.). Regressions (1) are "horse-race" (i.e. based on a full set of variables) while regressions (7) are based on a stepwise approach. For a detailed description of this stepwise approach, see footnote 2 in subsection 4.2. Main regressors are the set of CAMELS variables complemented by bank-specific control variables, as described in subsection 3.2. See table 3 for the matching between variable codes used in this table and their full names. Macro variables appearing in regressions (7) are not shown for the sake of brevity.

Table 13: Regressions by type of bank

cooperative banks. This implies that small cooperative banks that did not reach a "critical mass" may be too exposed to a local economic environment and less able to diversify risks, for instance geographically and/or in terms of economic sectors, and are therefore more vulnerable and prone to distress.

***Result n°6**: Overall, the main ex-ante drivers of distress seem to vary across our different types of bank depending on their ownership. Private banks' distress situations appear more driven by profitability and inter-bank liquidity metrics, while cooperative banks' distress tends to be more predicted by size or market risk metrics.*

Finally in this section, following Chatelain and Ralf [2021], we wonder whether pooled or separate estimations lead to the best predictions by type of bank. In table 14 we replicate the optimal probability cut-off selection based on the Youden Index made in table 8, but this time we allow the cut-off to vary across bank types. It appears that the optimal cut-off slightly changes for the three types of bank. Then in table 15 we compare the contingency matrices and efficiency metrics for pooled versus separate regressions for the three types of bank. Starting from the row showing the metrics for the optimal 5.5% cut-off for pooled estimations shown in table 8, we first break down these statistics by type of bank. Second, we show the same statistics obtained with the separate regressions (7) displayed in table 13 for the three types of bank with their own optimal probability cut-offs defined in table 14. Finally we compute the "total" row by simple aggregation of statistics for the separate estimations.

Prob.	Private banks			Cooperative banks			State-owned banks		
cut-off	Sensitivity	Specificity	Youden Index	Sensitivity	Specificity	Youden Index	Sensitivity	Specificity	Youden Index
4.50%	89.7%	24.6%	0.143	48.2%	83.8%	0.320	77.3%	60.3%	0.376
4.75%	86.3%	27.9%	0.142	46.4%	85.4%	0.319	77.3%	62.0%	0.392
5.00%	82.9%	31.2%	0.141	44.6%	86.6%	0.312	77.3%	63.9%	0.412
5.25%	80.3%	34.2%	0.146	44.6%	87.9%	0.325	77.3%	66.2%	0.435
5.50%	80.3%	37.9%	0.183	**44.6%**	**88.9%**	**0.336**	77.3%	67%	0.443
5.75%	79.5%	42.2%	0.217	39.3%	90.1%	0.294	77.3%	69.6%	0.469
6.00%	76.1%	45.5%	0.216	37.5%	90.9%	0.284	**77.3%**	**72.1%**	**0.494**
6.25%	71.8%	51.0%	0.228	37.5%	91.4%	0.289	72.7%	74.1%	0.468
6.50%	70.1%	54.7%	0.247	35.7%	91.9%	0.277	63.6%	74.9%	0.386
6.75%	**67.5%**	**58.6%**	**0.261**	33.9%	92.4%	0.263	63.6%	76.3%	0.400
7.00%	63.2%	61.3%	0.246	32.1%	92.9%	0.250	63.6%	77.7%	0.414

Note: For each type of bank, the bold cells indicate the probability cut-off that maximizes the Youden index (or Youden's J statistic), which is defined as $J = Sensitivity + Specificity - 1$.

Table 14: Optimal probability cut-off selection for separate estimations

We notice that the overall sensitivity increases from 57.4% to 62.1% when we use separate estimations and different probability cut-offs across bank types compared to pooled regressions, and this also improves the specificity from 71.7% to 75.0%. In details

Regression type	Banks	Prob. cut-off	Predicted Distress	Non-predicted Distress	False alarms	Predicted non-distress	Sensitivity	Specificity	Correctly classified obs.
Pooled	All, of which:	5.5%	112	83	1053	2677	57.4%	71.7%	71.1%
	Private	5.5%	78	39	693	820	66.7%	54.2%	55.1%
	Cooperative	5.5%	20	36	231	1631	35.7%	87.6%	86.1%
	State-owned	5.5%	14	8	129	226	63.6%	63.7%	63.7%
Separate	Private	6.75%	79	38	627	886	67.5%	58.6%	59.2%
	Cooperative	5.5%	25	31	206	1656	44.6%	88.9%	87.6%
	State-owned	6.0%	17	5	99	256	77.3%	72.1%	72.4%
	TOTAL		121	74	932	2798	62.1%	75%	74.4%

Table 15: Model's efficiency by type of bank for pooled and separate estimations

by type of bank, moving from pooled to separate estimations increases both sensitivity and specificity for the three types of bank.

***Result n°7**: Using separate estimations for private, cooperative and state-owned banks leads to better prediction results for all types of bank, compared to pooled estimations, so separate regressions should be preferred from an operational perspective.*

6 Robustness checks

6.1 Probit regressions

As a first robustness check, table 16 provides the same regressions as in table 6 but using probit regressions instead of logit. The overall results remain quite similar to those described in section 4.

6.2 Adding variables in first difference

As another robustness check, we can add to the regressions the list of explanatory CAMELS variables and additional control variables expressed in first difference. The purpose of this check is to assess whether sudden variations of these variables could be predictors of distress, on top of levels of these explanatory variables. Table 17 shows results of regressions (1) and (7) of the main results table (table 6) and replicate these two same regressions when first difference variables are added to the specification.

We notice that very few of the first difference variables appear significant, and that

	Dependent variable: DISTRESS						
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TOW Solv ratio (lag)	-0.091	-0.003			-0.099	-0.086	
	(0.101)	(0.076)			(0.101)	(0.102)	
LR B3 (lag)	-0.240		-0.152	-0.490**	-0.188	-0.182	-0.506**
	(0.342)		(0.262)	(0.246)	(0.343)	(0.340)	(0.247)
Share NPL (lag)	0.065	0.124			0.177	0.207	
	(0.319)	(0.275)			(0.330)	(0.327)	
PROV to TA (lag)	-1.311		-1.177	-2.042**	-1.301	-1.322	-1.989**
	(1.030)		(1.034)	(0.961)	(1.031)	(1.041)	(0.945)
Cosf Eff (lag)	-0.024	0.233***			-0.049	-0.042	
	(0.094)	(0.076)			(0.100)	(0.099)	
Pers Exp (lag)	0.304		0.276		0.472*	0.438	
	(0.258)		(0.220)		(0.268)	(0.267)	
PROF (lag)	-0.759	-0.416			-1.033**	-0.882*	
	(0.463)	(0.398)			(0.514)	(0.491)	
ROA (lag)	-4.646***	-2.803**	-6.850***	-6.625***	-4.140**	-4.193**	-6.471***
	(1.734)	(1.412)	(1.597)	(1.558)	(1.775)	(1.692)	(1.555)
Volatility of ROA (lag)	7.856***		7.481***	6.366***	8.739***	8.489***	6.623***
	(2.227)		(1.929)	(1.890)	(2.214)	(2.219)	(1.861)
LOAN to DEP (lag)	0.002	0.001	-0.000		0.002	0.002	
	(0.002)	(0.002)	(0.000)		(0.002)	(0.002)	
NSFR (lag)	-0.056		0.042**	-0.080**	-0.057	-0.056	-0.077**
	(0.037)		(0.019)	(0.035)	(0.038)	(0.038)	(0.036)
Share MRK RWA (lag)	0.040	0.340	0.219	0.178	0.238	0.144	
	(0.345)	(0.292)	(0.321)	(0.334)	(0.348)	(0.350)	
HFTA to TA (lag)	1.184*	0.664	0.544	0.691	1.122*	1.153*	0.778
	(0.618)	(0.661)	(0.561)	(0.677)	(0.626)	(0.629)	(0.570)
SIZE (lag)	-0.106***	-0.074***	-0.079***	-0.087***	-0.094***	-0.095***	-0.090***
	(0.020)	(0.023)	(0.023)	(0.018)	(0.020)	(0.020)	(0.019)
Net LOANS to TA (lag)	-0.918***	-0.463**	-0.461**	-0.853***	-0.921***	-0.902***	-0.800***
	(0.244)	(0.182)	(0.181)	(0.207)	(0.254)	(0.250)	(0.222)
Net LOANS to TA (lag)	0.038				0.037	0.044	
	(0.090)				(0.087)	(0.090)	
SEC HELD to TA (lag)	-0.070	-0.287	-0.257	-0.270	-0.085	-0.047	
	(0.250)	(0.221)	(0.221)	(0.224)	(0.257)	(0.255)	
DEP to TA (lag)	0.495*	0.314	0.275	0.301	0.483*	0.507*	
	(0.271)	(0.219)	(0.213)	(0.219)	(0.270)	(0.270)	
SEC ISSUED to TA (lag)	0.500	-0.112	-0.150	-0.106	0.528	0.536	
	(0.403)	(0.335)	(0.331)	(0.336)	(0.393)	(0.395)	
IBA to TA (lag)	-0.731***	-0.760***	-0.752***	-0.634***	-0.753***	-0.736***	-0.609***
	(0.239)	(0.195)	(0.194)	(0.204)	(0.246)	(0.244)	(0.213)
IBL to TA (lag)	0.319	0.509**	0.499**	0.528**	0.362	0.384	
	(0.289)	(0.259)	(0.254)	(0.259)	(0.287)	(0.288)	
Lerner Index (lag)	-0.247	-0.195	-0.245	-0.222	-0.124	-0.121	
	(0.230)	(0.177)	(0.175)	(0.175)	(0.248)	(0.246)	
Crisis			0.078			0.147	
			(0.139)			(0.194)	
ST Interest Rate (lag)				-0.007		0.043	
				(0.051)		(0.044)	
LT Interest Rate (lag)				-0.004		0.070	
				(0.083)		(0.080)	
Inflation (lag)				-0.320***		0.009	-0.152***
				(0.095)		(0.109)	(0.057)
Unemployment (lag)				-0.158***		0.153*	
				(0.054)		(0.083)	
GDP growth (lag)				5.962*		-6.766	
				(3.318)		(4.558)	
Intercept	0.301	-1.758***	-1.771***	0.319	-0.273	-1.721	0.538
	(0.441)	(0.059)	(0.069)	(0.353)	(0.493)	(1.126)	(0.368)
Bank-year observations	3,925	3,925	3,925	3,925	3,925	3,925	3,925
Area under ROC curve	0.6931	0.5651	0.6313	0.6863	0.727	0.7043	0.6941
Horse-race regression	YES	NO	NO	NO	YES	YES	NO
Split CAMELS	NO	YES	YES	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	YES	NO	NO	YES
Time fixed effects	NO	NO	NO	NO	YES	NO	NO
Macro variables	NO	NO	NO	NO	NO	YES	YES

Note: Probit regressions with robust standard errors clustered at bank level. Since this table shows the results of probit regressions, then the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks. Regressions can either be "horse-race" (i.e. based on a full set of variables), or restricted to half of the set of explanatory variables ("split CAMELS"), or even based on a stepwise approach. For a detailed description of this stepwise approach, see footnote 2 in subsection 4.2. Main regressors are the set of CAMELS variables complemented by bank-specific control variables, as described in subsection 3.2. See table 3 for the matching between variable codes used in this table and their full names. Time fixed effects or a set of macroeconomic time-varying control variables are added in some regressions.

Table 16: Robustness check: probit regressions

their inclusion does not change the magnitude nor the significance of the variables in level.

6.3 Testing longer lags

In this subsection we re-run regressions (1) and (7) shown in table 6 using longer time lags. In section 4.1, we explained that explanatory variables (both CAMELS and other bank-specific and macroeconomic control variables) are lagged by one period (i.e. one year). The purpose of this lag is twofold: from a technical perspective, it is meant to avoid potential endogeneity issues due to simultaneity with the dependent variable, and in the spirit of EWS models we try to identify *ex-ante* determinants of distress. However, those *ex-ante* drivers of distressed situations can also have some predictive power more than one year ahead of the events. Therefore we apply the same equation (1) described previously, but using lags of two, three and even four years. Table 18 provides the regression results we obtain with these longer lags.

We notice that some variables keep their predictive power two years ahead of the distress events (i.e. they remain significant explanatory variables when using a two-year lag instead of the standard one-year lag). This is the case of the provisioning ratio and the volatility of ROA. The ratio of held for trading assets remains a good ex-ante determinant of distress up to three years ahead. Finally three variables even retain a satisfying significance levels when applying four-year lags: the return on assets (ROA), the size of the bank and the share of loans within total assets.

6.4 Focusing on downgrades to rating 5

As described in section 3, the lowest possible rating is 5. In previous sections of this paper, a situation of "distress" was defined when the rating of a bank is downgraded from 1, 2 or 3 to 4 or 5 during the year. As a robustness check, we can restrict this definition to downgrades to rating 5. Using this more restrictive definition of "distress",

***Result n°8**: While the risk-weighted solvency ratio was generally not an efficient predictor of banks' distress, it seems that it is still a relevant variable for the most extreme distress cases.*

we narrow down the total number of distress events from 224 to 59. 42 distinct banks face such extreme downgrade in our panel (29 of them face only one downgrade to 5, while nine banks face this situation twice, and four banks are even downgraded to 5 three times over the full time-span of our panel). Table 19 replicates the results of table 6 with this more restrictive definition of the dependent variable, which implies that we focus here on the worst distress cases.

Compared to the results described in previous sections, we notice that now the total own funds solvency ratio becomes significant in most regressions, with the expected negative sign. This implies that better capitalized banks are much less likely to face this more severe distress situation (downgrade to rating 5).

The return on assets (ROA) and its volatility are still highly significant, respectively with the negative and positive expected sign. The size variable and the inter-bank asset ratio also remain good predictors of extreme distress.

7 Duration of distress

As an alternative approach to the one developed in previous sections of this paper, instead of focusing on the moment when a downgrade occurs (which defines the "distress" events), we can use the *duration* of the distress event as main variable. We still define a "distress" event as a downgrade of a bank's rating from 1, 2 or 3 to 4 or 5, and we measure the length before the rating goes back to 1, 2 or 3 (or before the entity disappears from the dataset). Figure 4 shows the distribution of the duration of the distress events. We notice that 35% of them only last one year, with only a minority exceeding four years.

Using the duration of distress events as dependent variable, and keeping the same set

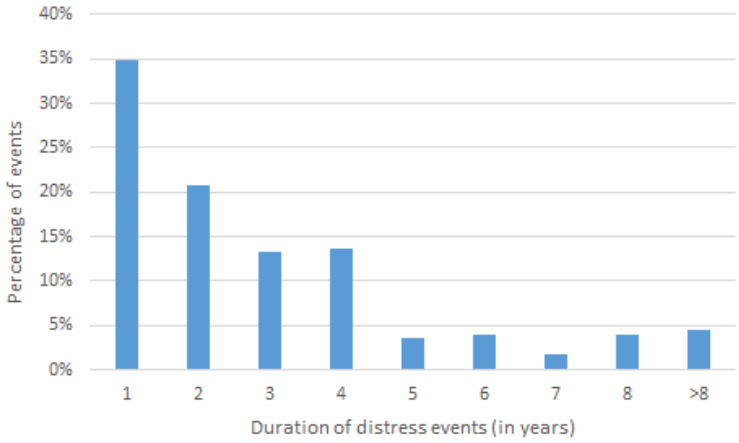

Figure 4: Distribution of duration of distress events

of lagged explanatory variables as described in previous sections, we apply the following specification:

$$Duration of Distress_{i,t} = \alpha + \beta_1 \cdot X_{i,t-1} + \beta_2 \cdot BC_{i,t-1} + \beta_3 \cdot M_{t-1} + u_{i,t}$$

Table 20 displays the results for this specification. It turns out that size of banks has a significant negative impact on the duration of distress events, meaning that, everything else equal, when larger banks face a distress situation they are less likely to enter a long-lasting period of distress than smaller banks. We find that a larger volatility of the ROA significantly increases the duration of distress, as banks with more unstable results will have more difficulties to restore a sound situation. We also notice that a higher NSFR will reduce the length of such distress periods. Finally, the more a distressed bank holds intra-bank assets, the shorter its distress events, as these assets are usually of short maturity and can promptly be converted into cash to restructure the balance sheet.

8 Concluding remarks

This paper builds on an innovative data source to assess the relevance of an early warning system for the French banking sector. In order to identify "distressed" banks, we used an internal rating that has been at the core of the supervisory process of the French prudential and resolution authority between 1997 and 2013. We also collected a dataset that comprises the set of CAMELS variables commonly used in the literature, that we complemented with other bank-specific control variables, such as inter-bank liquidity variables. Using this unbalanced panel of 5,042 bank-year observations, we applied a usual multivariate logit regression methodology to assess which banks' ex-ante characteristics are good predictors of a distressed situation.

Our regression results bring general support to the usual set of CAMELS variables in an early warning system for the French banking sector. These variables display the expected sign in most of the regressions, although not all of them appear to be significant. We show that the main determinants of distress are the level of profitability of banks' assets measured by the ROA, as well as its volatility. Everything else equal, a bank with higher and more stable profitability is less likely to face a distressed situation.

Surprisingly, capital adequacy ratios (the total own funds solvency ratio and the Basel III leverage ratio) generally do not appear as efficient predictors of banks' distress. This might be an application of "Goodhart's law", which states that when an indicator becomes a policy target, it ceases to be a good predictive measure. Knowing that capital adequacy ratios are priority indicators with strong minimum requirements to be observed under the prudential regulation, it is then not so surprising that they lost their predictive power in such an EWS model. However, once we restrict the analysis to the most extreme distress cases, the total own funds solvency ratio finally becomes an

efficient predictor.

This paper also shows that it is relevant to take into account other indicators besides usual CAMELS variables. For instance, we find that an inter-bank liquidity variable is an efficient predictor in an early warning system for French banks. More specifically, our results tend to bring support to a liquidity management rationale: if a bank lends extra cash to other banks, generally through short-term operations, such as repurchase agreements, they can easily stop renewing these operations and use this cash to restructure their balance sheet if they face a distress situation. So larger inter-bank assets decrease the probability of distress.

These drivers of vulnerability are identified using a one-year lag, meaning that they are good predictors of distress situations one year ahead of the events. However, as we also tested longer lags, we show that many of these drivers keep some significant predictive power with two or three-year lags, and even up to four-year lags for the ROA and the size variables.

Taking into account one of the major specificity of the French banking sector, we analyze whether these drivers of bank distress are similar across the different types of bank, depending on their ownership. We find empirical evidence that determinants of distress events actually vary between bank types. Private banks' distress situations seem more driven by lack of profitability and/or excessive volatility of returns, while cooperative banks' events appear more predicted by the size of the entity and its sensitivity to market risk.

Finally, we noticed that the efficiency of our EWS model appears rather satisfying as more than 70% of observations are correctly classified one year ahead. Nevertheless, the

limitations of such model also illustrate that there remains a discretionary dimension in the assessment made by the supervisor. Based on their deep knowledge of banks' activity and their access to qualitative information, banking supervisors are able to take into account various other elements than quantitative accounting ratios into their final rating which reflects the overall situation of the assessed bank. Therefore, in terms of policy implications, this paper reveals the relevance of using such an early warning system as a basis or a complement to the assessment of banks' individual situation made by supervisors.

Dependent variable: DISTRESS				
Regression	(1)	(1) with Δ	(7)	(7) with Δ
TOW Solv ratio (lag)	-0.177	-0.210		
TOW Solv ratio (Δ)		0.031		
LR B3 (lag)	-0.481	-0.157	-0.939*	-1.194**
LR B3 (Δ)		-1.191		
Share NPL (lag)	0.197	0.574		
Share NPL (Δ)		1.830**		1.600*
PROV to TA (lag)	-2.647	-2.828	-3.833*	-3.465*
PROV to TA (Δ)		8.797*		7.667*
Cosf Eff (lag)	-0.023	-0.136		
Cosf Eff (Δ)		-0.272		
Pers Exp (lag)	0.564	0.783		
Pers Exp (Δ)		1.082		
PROF (lag)	-1.542	-1.299		
PROF (Δ)		-1.411		
ROA (lag)	-8.935***	-10.769***	-12.029***	-14.23***
ROA (Δ)		-4.124		-6.014*
Volatility of ROA (lag)	14.177***	15.303***	12.027***	12.82***
Volatility of ROA (Δ)		4.609		
LOAN to DEP (lag)	0.005	-0.001		
LOAN to DEP (Δ)		-0.021***		-0.017***
NSFR (lag)	-0.118	-0.110	-0.151**	
NSFR (Δ)		0.185		0.266**
Share MRK RWA (lag)	-0.001	-0.092		
Share MRK RWA (Δ)		0.787		
HFTA to TA (lag)	2.486**	3.301**	1.818	3.243***
HFTA to TA (Δ)		2.023		
SIZE (lag)	-0.222***	-0.221***	-0.187***	-0.186***
SIZE (Δ)		-0.165		
Net LOANS to TA (lag)	-1.925***	-1.794***	-1.568***	
Net LOANS to TA (Δ)		-1.438		
Credit Growth (lag)	0.086	0.208		
Credit Growth (Δ)		0.058		
SEC HELD to TA (lag)	-0.126	-0.058		
SEC HELD to TA (Δ)		-1.080		
DEP to TA (lag)	1.031*	1.310**		
DEP to TA (Δ)		-0.196		
SEC ISSUED to TA (lag)	0.950	1.023		
SEC ISSUED to TA (Δ)		-3.152*		-3.232**
IBA to TA (lag)	-1.497***	-1.528***	-1.187***	
IBA to TA (Δ)		-0.361		
IBL to TA (lag)	0.704	1.091*		
IBL to TA (Δ)		0.544		
Lerner Index (lag)	-0.480	-0.341		
Lerner Index (Δ)		1.171		1.334***
Intercept	1.093	0.598	-1.221	-2.791***
Bank-year observations	3,925	3,907	3,925	3,907
Area under ROC curve	0.6925	0.7334	0.6906	0.7130
Horse-race regression	YES	YES	NO	NO
Split CAMELS	NO	NO	NO	NO
Stepwise regression	NO	NO	YES	YES
Time fixed effects	NO	NO	NO	NO
Macro variables	NO	NO	YES	YES

Note: Logistic regressions with robust standard errors clustered at bank level. Since this table shows the results of logit regressions, then the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks. See table 3 for the matching between variable codes used in this table and their full names. The Δ sign indicates variables measured in first difference. Macroeconomic variables are included in the stepwise process for regressions (7) but are not shown in this table for the sake of brevity.

Table 17: Robustness check: adding variables in first difference

	Dependent variable: DISTRESS							
Regression	(1)				(7)			
Lags	$t-1$	$t-2$	$t-3$	$t-4$	$t-1$	$t-2$	$t-3$	$t-4$
TOW Solv ratio (lag X)	-0.177	-0.262	0.041	0.143		-0.592**		
	(0.208)	(0.228)	(0.210)	(0.228)		(0.233)		
LR B3 (lag X)	-0.481	-0.334	-0.586	-0.487	-0.939*			
	(0.707)	(0.827)	(0.886)	(0.969)	(0.508)			
Share NPL (lag X)	0.197	0.223	-0.438	0.731				
	(0.644)	(0.943)	(0.994)	(1.178)				
PROV to TA (lag X)	-2.647	-2.249	0.121	-0.015	-3.833*	-4.400**		
	(2.218)	(2.132)	(2.158)	(2.418)	(1.976)	(2.069)		
Cosf Eff (lag X)	-0.023	-0.448	-0.786*	-0.539				
	(0.177)	(0.290)	(0.419)	(0.347)				
Pers Exp (lag X)	0.564	1.347*	2.573***	1.961**				
	(0.509)	(0.695)	(0.904)	(0.964)				
PROF (lag X)	-1.542	-1.578	-2.388	-0.324				
	(0.941)	(1.364)	(1.585)	(1.493)				
ROA (lag X)	-8.935***	-4.477	-0.987	-7.201	-12.029***	-7.715***	-7.367**	-9.437*
	(3.317)	(3.192)	(4.341)	(6.235)	(2.940)	(2.889)	(3.482)	(4.942)
Volatility of ROA (lag X)	14.177***	17.142***	14.614**	10.814	12.027***	10.929**		
	(4.094)	(5.179)	(6.006)	(8.642)	(3.435)	(4.493)		
LOAN to DEP (lag X)	0.005	0.000	0.001	0.003				
	(0.005)	(0.006)	(0.006)	(0.006)				
NSFR (lag X)	-0.118	-0.091	-0.032	0.008	-0.151**			
	(0.077)	(0.088)	(0.090)	(0.105)	(0.076)			
Share MRK RWA (lag X)	-0.001	0.696	0.915	0.965				
	(0.766)	(0.593)	(0.608)	(0.696)				
HFTA to TA (lag X)	2.486**	3.586***	2.541*	0.017	1.818	3.892***	2.701**	
	(1.214)	(1.254)	(1.404)	(1.786)	(1.130)	(1.154)	(1.276)	
SIZE (lag X)	-0.222***	-0.218***	-0.188***	-0.139***	-0.187***	-0.183***	-0.140***	-0.117***
	(0.043)	(0.047)	(0.052)	(0.054)	(0.040)	(0.043)	(0.040)	(0.041)
Net LOANS to TA (lag X)	-1.925***	-1.739***	-1.955***	-1.684**	-1.568***	-0.596*	-1.469***	-0.639*
	(0.505)	(0.584)	(0.599)	(0.697)	(0.462)	(0.305)	(0.395)	(0.329)
Credit Growth (lag X)	0.086	0.023	0.443**	0.194			0.410**	
	(0.195)	(0.176)	(0.194)	(0.199)			(0.176)	
SEC HELD to TA (lag X)	-0.126	-0.373	-0.712	-1.288**			-0.857*	
	(0.508)	(0.596)	(0.625)	(0.644)			(0.519)	
DEP to TA (lag X)	1.031*	0.640	0.821	0.755				
	(0.572)	(0.678)	(0.757)	(0.885)				
SEC ISSUED to TA (lag X)	0.950	1.496	1.431	1.425				
	(0.870)	(1.050)	(1.171)	(1.274)				
IBA to TA (lag X)	-1.497***	-1.282**	-1.734***	-1.627**	-1.187***		-1.274**	
	(0.484)	(0.612)	(0.644)	(0.708)	(0.438)		(0.525)	
IBL to TA (lag X)	0.704	1.127	1.121	0.644				
	(0.617)	(0.723)	(0.797)	(0.903)				
Lerner Index (lag X)	-0.480	0.254	-0.275	-0.423				
	(0.502)	(0.614)	(0.640)	(0.611)				
Crisis								
ST Interest Rate (lag X)					0.105*			
					(0.056)			
LT Interest Rate (lag X)						0.327**	0.256*	
						(0.128)	(0.153)	
Inflation (lag X)								
Unemployment (lag X)					0.204***			
					(0.067)			
GDP growth (lag X)								14.85*
								(7.785)
Intercept	1.093	0.325	0.042	-0.603	-1.221	-1.615**	-1.269	-1.504***
	(0.930)	(1.154)	(1.325)	(1.339)	(1.043)	(0.786)	(0.928)	(0.563)
Bank-year observations	3,925	3,492	3,104	2,744	3,925	3,492	3,104	2,744
Area under ROC curve	0.6925	0.6947	0.6974	0.6641	0.6906	0.6776	0.667	0.6376
Horse-race regression	YES	YES	YES	YES	NO	NO	NO	NO
Split CAMELS	NO	NO	NO	NO	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	NO	YES	YES	YES	YES
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO
Macro variables	NO	NO	NO	NO	YES	YES	YES	YES

Note: Logistic regressions with robust standard errors clustered at bank level. Since this table shows the results of logit regressions, then the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks. See table 3 for the matching between variable codes used in this table and their full names.

Table 18: Robustness check: testing longer lags

	Dependent variable: Downgrade to rating 5						
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TOW Solv ratio (lag)	-1.535*	-0.393		-1.542**	-1.511*	-1.435*	-1.521**
	(0.886)	(0.305)		(0.670)	(0.897)	(0.831)	(0.661)
LR B3 (lag)	0.870		-0.782		0.923	0.895	
	(1.471)		(1.183)		(1.461)	(1.411)	
Share NPL (lag)	1.186	1.015			1.577	1.672	
	(1.057)	(0.711)			(1.104)	(1.161)	
PROV to TA (lag)	-5.165		-0.349		-4.399	-4.567	
	(5.162)		(3.399)		(5.013)	(4.947)	
Cosf Eff (lag)	-0.248	0.669***			-0.412	-0.371	
	(0.356)	(0.208)			(0.454)	(0.411)	
Pers Exp (lag)	1.629		1.346*		2.100*	2.083*	
	(1.085)		(0.743)		(1.248)	(1.156)	
PROF (lag)	-5.373	-0.947		-1.279	-6.595	-6.201	
	(3.959)	(1.896)		(1.519)	(4.464)	(4.311)	
ROA (lag)	-7.929**	-6.877*	-10.536***	-12.749***	-7.129	-6.672*	-12.041***
	(3.886)	(3.909)	(3.549)	(2.958)	(4.335)	(4.030)	(2.998)
Volatility of ROA (lag)	25.426***		20.824***	15.618***	27.271***	26.431***	16.522***
	(5.738)		(5.515)	(5.407)	(6.014)	(5.841)	(5.463)
LOAN to DEP (lag)	-0.005	-0.001	-0.006*	-0.006*	-0.008	-0.006	
	(0.011)	(0.009)	(0.003)	(0.003)	(0.011)	(0.011)	
NSFR (lag)	-0.218		0.041		-0.217	-0.205	
	(0.192)		(0.116)		(0.208)	(0.202)	
Share MRK RWA (lag)	0.891	1.531	1.215	1.438	1.515	1.363	1.506*
	(1.101)	(0.944)	(0.907)	(0.969)	(1.176)	(1.157)	(0.912)
HFTA to TA (lag)	2.642	-0.596	1.415	4.290*	2.501	2.493	4.230*
	(2.480)	(3.843)	(2.495)	(2.387)	(2.559)	(2.460)	(2.422)
SIZE (lag)	-0.311***	-0.126	-0.141	-0.302***	-0.294***	-0.286***	-0.298***
	(0.085)	(0.103)	(0.102)	(0.067)	(0.086)	(0.087)	(0.068)
Net LOANS to TA (lag)	-2.019*	-1.319*	-1.338*	-1.324*	-1.951	-1.882	
	(1.106)	(0.779)	(0.764)	(0.786)	(1.233)	(1.204)	
Credit Growth (lag)	-0.238				-0.176	-0.220	
	(0.318)				(0.292)	(0.301)	
SEC HELD to TA (lag)	0.701	-0.611	-0.490	-0.615	0.559	0.641	
	(0.989)	(1.038)	(1.021)	(1.065)	(1.073)	(1.063)	
DEP to TA (lag)	0.893	-0.119	-0.087	-0.128	0.701	0.808	
	(1.253)	(0.981)	(0.991)	(0.985)	(1.158)	(1.172)	
SEC ISSUED to TA (lag)	-0.275	-3.895*	-3.860**	-3.930**	-0.389	-0.295	
	(1.507)	(2.015)	(1.956)	(1.995)	(1.490)	(1.512)	
IBA to TA (lag)	-1.999*	-2.580***	-2.529***	-2.582***	-1.901*	-1.935*	
	(1.035)	(0.973)	(0.949)	(0.971)	(1.085)	(1.086)	
IBL to TA (lag)	1.500	0.853	0.831	0.834	1.480	1.514	
	(1.223)	(0.954)	(0.953)	(0.955)	(1.161)	(1.185)	
Lerner Index (lag)	0.518	-0.114	-0.226	-0.131	0.719	0.781	
	(0.990)	(0.773)	(0.723)	(0.756)	(1.057)	(1.004)	
Crisis			0.183			0.901	
			(0.475)			(0.923)	
ST Interest Rate (lag)				0.138		0.159	
				(0.177)		(0.192)	
LT Interest Rate (lag)				-0.107		0.134	
				(0.323)		(0.360)	
Inflation (lag)				-0.971**		-0.217	-0.583**
				(0.393)		(0.512)	(0.237)
Unemployment (lag)				-0.257		0.459	
				(0.216)		(0.374)	
GDP growth (lag)				1.207		-25.571	
				(8.776)		(18.31)	
Intercept	0.451	-4.635***	-4.822***	-0.163	-0.687	-4.824	0.632
	(1.933)	(0.234)	(0.286)	(0.985)	(2.255)	(5.120)	(0.991)
Bank-year observations	3,925	3,925	3,925	3,925	3,642	3,925	3,925
Area under ROC curve	0.8078	0.6639	0.7477	0.7795	0.8574	0.8455	0.8005
Horse-race regression	YES	NO	NO	NO	YES	YES	NO
Split CAMELS	NO	YES	YES	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	YES	NO	NO	YES
Time fixed effects	NO	NO	NO	NO	YES	NO	NO
Macro variables	NO	NO	NO	NO	NO	YES	YES

Note: Logistic regressions with robust standard errors clustered at bank level. This table shows the results of logit regressions, then the magnitude of the coefficients cannot be directly interpreted, only their signs and significance levels can. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks. Regressions can either be "horse-race" (i.e. based on a full set of variables), or restricted to half of the set of explanatory variables ("split CAMELS"), or even based on a stepwise approach. For a detailed description of this stepwise approach, see footnote 2 in subsection 4.2. Main regressors are the set of CAMELS variables complemented by bank-specific control variables, as described in subsection 3.2. See table 3 for the matching between variable codes used in this table and their full names. Time fixed effects or a set of macroeconomic time-varying control variables are added in some regressions.

Table 19: Robustness check: downgrade to rating 5

	Dependent variable: Duration of distress events						
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TOW Solv ratio (lag)	-0.029	-0.021		-0.013	-0.034	-0.033	-0.025
	(0.029)	(0.023)		(0.022)	(0.029)	(0.029)	(0.022)
LR B3 (lag)	0.112		-0.094		0.052	0.045	
	(0.178)		(0.128)		(0.174)	(0.173)	
Share NPL (lag)	0.395***	0.224		0.355***	0.220*	0.213*	
	(0.137)	(0.142)		(0.134)	(0.119)	(0.120)	
PROV to TA (lag)	0.122		-0.151		0.173	0.212	
	(0.300)		(0.255)		(0.295)	(0.300)	
Cosf Eff (lag)	-0.045	0.124**		-0.068*	-0.060*	-0.057	
	(0.038)	(0.049)		(0.037)	(0.036)	(0.036)	
Pers Exp (lag)	0.551***		0.418***	0.593***	0.513***	0.504***	0.359***
	(0.147)		(0.124)	(0.145)	(0.142)	(0.140)	(0.123)
PROF (lag)	-0.513**	-0.181		-0.524***	-0.521***	-0.517**	-0.468**
	(0.227)	(0.123)		(0.184)	(0.201)	(0.208)	(0.185)
ROA (lag)	-0.353		-1.787***		-0.124	-0.159	-0.420
	(0.832)		(0.655)		(0.848)	(0.839)	(0.764)
Volatility of ROA (lag)	4.533***		3.538***	4.829***	4.030***	3.908***	3.376***
	(1.168)		(0.931)	(1.174)	(1.129)	(1.137)	(0.968)
LOAN to DEP (lag)	0.000	-0.001			0.000	0.000	
	(0.001)	(0.001)			(0.001)	(0.001)	
NSFR (lag)	-0.043***		-0.002	-0.048***	-0.050***	-0.052***	-0.064***
	(0.015)		(0.007)	(0.014)	(0.016)	(0.016)	(0.015)
Share MRK RWA (lag)	0.005	0.061			0.079	0.161	
	(0.139)	(0.120)			(0.143)	(0.148)	
HFTA to TA (lag)	0.403		0.268		0.471	0.461	
	(0.326)		(0.281)		(0.325)	(0.331)	
SIZE (lag)	-0.023***			-0.024***	-0.037***	-0.037***	-0.031***
	(0.007)			(0.007)	(0.008)	(0.008)	(0.007)
Net LOANS to TA (lag)	-0.507***			-0.505***	-0.591***	-0.595***	-0.588***
	(0.139)			(0.122)	(0.139)	(0.141)	(0.129)
Credit Growth (lag)	0.014				0.032	0.028	
	(0.026)				(0.026)	(0.026)	
SEC HELD to TA (lag)	-0.065				-0.126	-0.150	
	(0.106)				(0.109)	(0.112)	
DEP to TA (lag)	0.422***			0.381***	0.375***	0.366***	0.270***
	(0.141)			(0.117)	(0.138)	(0.138)	(0.096)
SEC ISSUED to TA (lag)	0.292*			0.245*	0.250*	0.241	
	(0.150)			(0.132)	(0.150)	(0.150)	
IBA to TA (lag)	-0.475***			-0.495***	-0.528***	-0.541***	-0.499***
	(0.128)			(0.116)	(0.125)	(0.128)	(0.119)
IBL to TA (lag)	0.320**			0.267**	0.265*	0.258*	0.164*
	(0.139)			(0.113)	(0.138)	(0.137)	(0.088)
Lerner Index (lag)	0.100				-0.111	-0.122	
	(0.106)				(0.103)	(0.100)	
Crisis						0.113*	
						(0.058)	
ST Interest Rate (lag)						0.031	
						(0.020)	
LT Interest Rate (lag)						-0.151***	-0.164***
						(0.036)	(0.028)
Inflation (lag)						0.151***	
						(0.050)	
Unemployment (lag)						0.131***	
						(0.038)	
GDP growth (lag)						-6.540***	
						(1.850)	
Intercept	0.487***	0.121***	0.078***	0.598***	1.634***	0.113	1.572***
	(0.168)	(0.022)	(0.024)	(0.138)	(0.302)	(0.408)	(0.247)
Bank-year observations	3,925	3,925	3,925	3,925	3,925	3,925	3,925
Horse-race regression	YES	NO	NO	NO	YES	YES	NO
Split CAMELS	NO	YES	YES	NO	NO	NO	NO
Stepwise regression	NO	NO	NO	YES	NO	NO	YES
Time fixed effects	NO	NO	NO	NO	YES	NO	NO
Macro variables	NO	NO	NO	NO	NO	YES	YES

Note: Random effect estimations with robust standard errors clustered at bank level. Regressions based on a bank-level unbalanced panel at annual frequency that contains 449 distinct banks. Regressions can either be "horse-race" (i.e. based on a full set of variables), or restricted to half of the set of explanatory variables ("split CAMELS"), or even based on a stepwise approach. For a detailed description of this stepwise approach, see footnote 2 in subsection 4.2. Main regressors are the set of CAMELS variables complemented by bank-specific control variables, as described in subsection 3.2. See table 3 for the matching between variable codes used in this table and their full names. Time fixed effects or a set of macroeconomic time-varying control variables are added in some regressions.

Table 20: Regression using duration of distress events as dependent variable

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Appendices

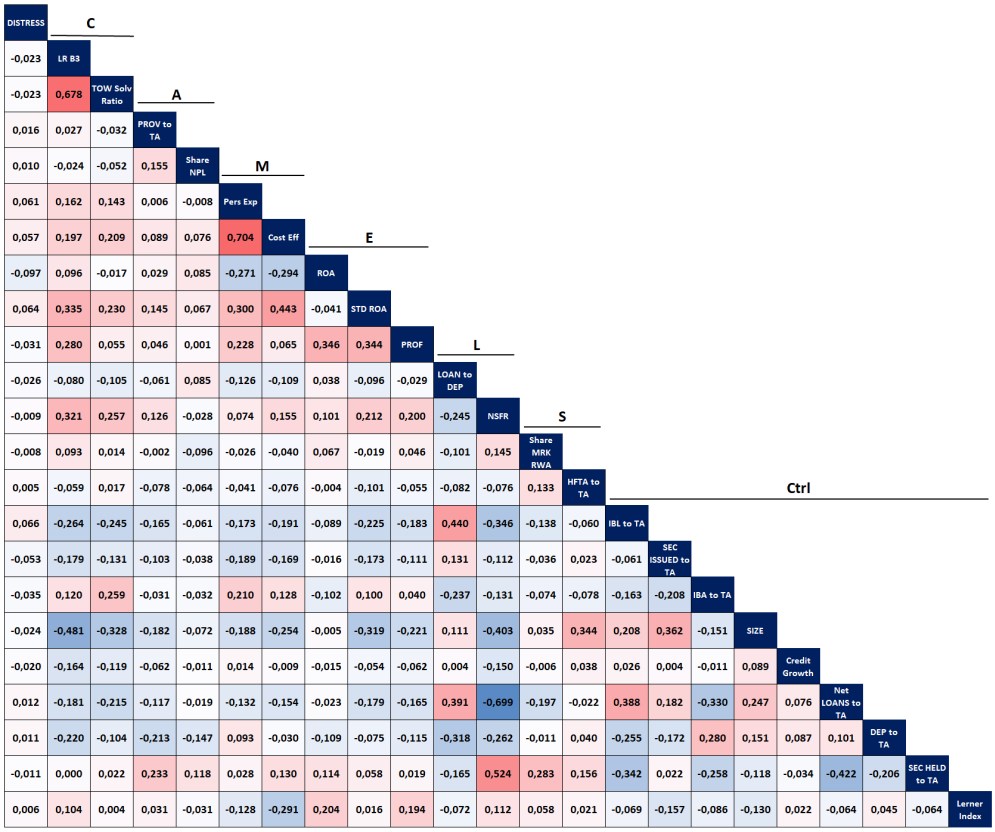
Appendix 1 - Correlation matrices

DISTRESS	C			A		M		E			L		S		Ctrl															
0,006	LR B3																													
-0,005	0,629	TOW Solv Ratio																												
0,020	0,019	0,046	Share NPL																											
0,018	0,114	0,028	0,134	PROV to TA																										
0,060	0,289	0,213	0,082	0,152	Cost Eff																									
0,059	0,275	0,142	0,014	0,085	0,696	Pers Exp																								
-0,075	0,138	0,023	0,064	0,036	-0,227	-0,207	ROA																							
0,065	0,421	0,277	0,082	0,210	0,437	0,268	0,049	STD ROA																						
-0,009	0,298	0,091	0,011	0,106	0,136	0,251	0,351	0,381	PROF																					
0,021	0,323	0,272	0,002	0,265	0,216	0,088	0,110	0,325	0,246	NSFR																				
-0,015	0,075	-0,017	0,104	-0,008	-0,027	-0,049	0,052	0,009	0,017	-0,157	LOAN to DEP																			
0,014	0,076	0,040	-0,073	0,014	-0,010	-0,026	0,067	0,035	0,068	0,165	-0,079	Share MRK RWA																		
0,014	-0,057	0,002	-0,055	-0,064	-0,074	-0,065	-0,008	-0,061	-0,046	-0,037	-0,069	0,178	HFTA to TA																	
-0,059	-0,549	-0,366	-0,114	-0,281	-0,347	-0,305	-0,063	-0,396	-0,288	-0,495	-0,089	0,003	0,268	SIZE																
-0,049	-0,196	-0,283	-0,103	-0,213	-0,185	-0,085	-0,043	-0,304	-0,198	-0,730	0,239	-0,249	-0,090	0,367	Net LOANS to TA															
-0,027	-0,159	-0,142	-0,026	-0,086	-0,043	-0,015	-0,029	-0,099	-0,070	-0,160	-0,019	-0,003	0,056	0,132	0,102	Credit Growth														
-0,024	-0,173	-0,104	-0,048	-0,100	-0,172	-0,202	-0,025	-0,138	-0,103	-0,086	0,110	-0,010	0,079	0,311	0,072	0,020	SEC ISSUED to TA													
0,012	0,042	0,050	0,070	0,292	0,164	0,047	0,087	0,123	0,063	0,589	-0,126	0,290	0,213	-0,176	-0,468	-0,032	0,046	SEC HELD to TA												
0,010	0,158	0,025	-0,002	0,072	-0,172	-0,007	0,188	0,090	0,214	0,158	-0,013	0,033	0,015	-0,208	-0,027	0,018	-0,143	-0,031	Lerner Index											
0,004	-0,301	-0,212	-0,158	-0,249	-0,078	0,055	-0,124	-0,211	-0,161	-0,350	-0,364	-0,020	-0,013	0,327	0,230	0,107	-0,116	-0,229	-0,021	DEP to TA										
-0,002	-0,287	-0,191	-0,051	-0,201	-0,233	-0,238	-0,076	-0,239	-0,190	-0,346	0,302	-0,154	-0,093	0,219	0,377	0,012	-0,133	-0,341	-0,127	-0,315	IBL to TA									
0,001	0,106	0,307	0,107	0,009	0,119	0,149	-0,066	0,132	0,045	-0,007	-0,188	0,003	-0,058	-0,141	-0,452	-0,041	-0,109	-0,158	-0,132	0,167	-0,219	IBA to TA								

Matrix of correlations between variables used in the regressions - All banks

The gradient of colors from blue to red respectively indicates highest negative / positive correlations.

For each CAMELS category and controls, variables are sorted by decreasing absolute value of correlation coefficient with the "Distress" variable.

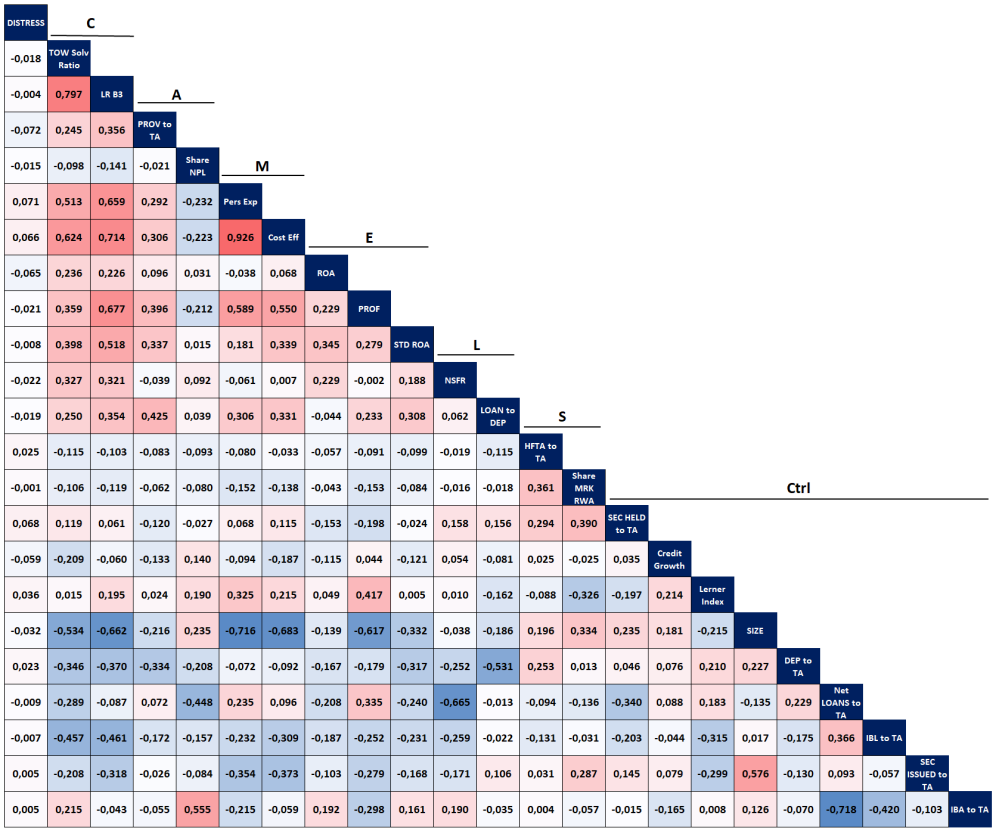


DISTRESS	C		A		M		E			L		S		Ctrl										
-0,023	LR B3																							
-0,023	0,678	TOW Solv Ratio																						
0,016	0,027	-0,032	PROV to TA																					
0,010	-0,024	-0,052	0,155	Share NPL																				
0,061	0,162	0,143	0,006	-0,008	Pers Exp																			
0,057	0,197	0,209	0,089	0,076	0,704	Cost Eff																		
-0,097	0,096	-0,017	0,029	0,085	-0,271	-0,294	ROA																	
0,064	0,335	0,230	0,145	0,067	0,300	0,443	-0,041	STD ROA																
-0,031	0,280	0,055	0,046	0,001	0,228	0,065	0,346	0,344	PROF															
-0,026	-0,080	-0,105	-0,061	0,085	-0,126	-0,109	0,038	-0,096	-0,029	LOAN to DEP														
-0,009	0,321	0,257	0,126	-0,028	0,074	0,155	0,101	0,212	0,200	-0,245	NSFR													
-0,008	0,093	0,014	-0,002	-0,096	-0,026	-0,040	0,067	-0,019	0,046	-0,101	0,145	Share MRK RWA												
0,005	-0,059	0,017	-0,078	-0,064	-0,041	-0,076	-0,004	-0,101	-0,055	-0,082	-0,076	0,133	HFTA to TA											
0,066	-0,264	-0,245	-0,165	-0,061	-0,173	-0,191	-0,089	-0,225	-0,183	0,440	-0,346	-0,138	-0,060	IBL to TA										
-0,053	-0,179	-0,131	-0,103	-0,038	-0,189	-0,169	-0,016	-0,173	-0,111	0,131	-0,112	-0,036	0,023	-0,061	SEC ISSUED to TA									
-0,035	0,120	0,259	-0,031	-0,032	0,210	0,128	-0,102	0,100	0,040	-0,237	-0,131	-0,074	-0,078	-0,163	-0,208	IBA to TA								
-0,024	-0,481	-0,328	-0,182	-0,072	-0,188	-0,254	-0,005	-0,319	-0,221	0,111	-0,403	0,035	0,344	0,208	0,362	-0,151	SIZE							
-0,020	-0,164	-0,119	-0,062	-0,011	0,014	-0,009	-0,015	-0,054	-0,062	0,004	-0,150	-0,006	0,038	0,026	0,004	-0,011	0,089	Credit Growth						
0,012	-0,181	-0,215	-0,117	-0,019	-0,132	-0,154	-0,023	-0,179	-0,165	0,391	-0,699	-0,197	-0,022	0,388	0,182	-0,330	0,247	0,076	Net LOANS to TA					
0,011	-0,220	-0,104	-0,213	-0,147	0,093	-0,030	-0,109	-0,075	-0,115	-0,318	-0,262	-0,011	0,040	-0,255	-0,172	0,280	0,151	0,087	0,101	DEP to TA				
-0,011	0,000	0,022	0,233	0,118	0,028	0,130	0,114	0,058	0,019	-0,165	0,524	0,283	0,156	-0,342	0,022	-0,258	-0,118	-0,034	-0,422	-0,206	SEC HELD to TA			
0,006	0,104	0,004	0,031	-0,031	-0,128	-0,291	0,204	0,016	0,194	-0,072	0,112	0,058	0,021	-0,069	-0,157	-0,086	-0,130	0,022	-0,064	0,045	-0,064	Lerner Index		

Matrix of correlations between variables used in the regressions - Private banks

The gradient of colors from blue to red respectively indicates highest negative / positive correlations.

For each CAMELS category and controls, variables are sorted by decreasing absolute value of correlation coefficient with the "Distress" variable.



Matrix of correlations between variables used in the regressions - State-owned banks

The gradient of colors from blue to red respectively indicates highest negative / positive correlations.

For each CAMELS category and controls, variables are sorted by decreasing absolute value of correlation coefficient with the "Distress" variable.

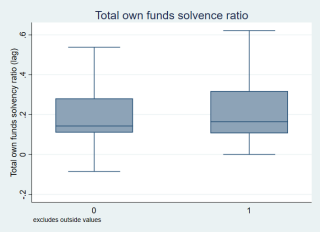
DISTRESS	C			A		M		E			L		S		Ctrl											
-0,023	LR B3																									
-0,018	0,481	TOW Solv Ratio																								
0,035	0,026	0,236	Share NPL																							
0,007	0,157	0,046	0,113	PROV to TA																						
0,008	-0,002	-0,121	0,113	0,299	Pers Exp																					
0,007	0,286	-0,003	0,155	0,317	0,595	Cost Eff																				
-0,065	0,239	0,028	-0,102	-0,074	-0,061	-0,003	ROA																			
-0,020	0,209	-0,004	0,002	0,279	0,236	0,251	0,367	PROF																		
-0,005	0,501	0,168	0,045	0,286	-0,006	0,189	0,299	0,338	STD ROA																	
-0,022	-0,015	-0,024	0,113	-0,070	-0,184	0,001	0,136	0,055	0,012	LOAN to DEP																
0,017	0,363	0,191	-0,020	0,709	0,104	0,264	0,040	0,224	0,420	-0,130	NSFR															
0,050	-0,054	0,031	-0,066	-0,035	-0,080	-0,052	-0,052	-0,079	-0,023	-0,085	0,024	Share MRK RWA														
0,020	-0,102	-0,033	-0,042	-0,059	-0,151	-0,138	-0,052	-0,094	-0,040	-0,047	-0,034	0,357	HFTA to TA													
-0,075	-0,168	-0,281	-0,105	-0,446	-0,021	-0,114	0,099	-0,093	-0,273	0,227	-0,699	-0,283	-0,140	Net LOANS to TA												
0,047	-0,252	-0,221	-0,097	-0,290	0,225	0,006	-0,152	-0,151	-0,251	-0,352	-0,389	0,106	-0,086	0,214	DEP to TA											
-0,046	-0,131	0,025	0,079	-0,256	-0,332	-0,238	0,080	-0,103	-0,089	0,319	-0,262	-0,166	-0,118	0,265	-0,590	IBL to TA										
0,039	0,109	0,378	0,203	0,086	0,090	0,049	-0,104	-0,023	0,063	-0,180	0,063	0,197	-0,052	-0,568	0,152	-0,215	IBA to TA									
-0,030	-0,420	-0,248	-0,186	-0,515	-0,269	-0,395	-0,053	-0,310	-0,307	-0,160	-0,604	0,193	0,341	0,367	0,317	0,065	-0,106	SIZE								
-0,029	0,102	-0,039	-0,117	0,159	0,134	-0,011	0,124	0,179	0,159	0,099	0,193	-0,151	0,001	0,145	-0,063	-0,100	-0,337	-0,193	Lerner Index							
-0,018	-0,202	-0,153	-0,148	-0,166	-0,027	-0,108	-0,040	-0,056	-0,249	-0,021	-0,227	0,073	0,145	0,160	0,136	-0,067	-0,084	0,193	-0,001	Credit Growth						
0,017	-0,148	-0,041	-0,051	-0,133	-0,213	-0,192	-0,052	-0,107	-0,078	0,089	-0,052	0,040	0,176	-0,046	-0,061	-0,246	0,048	0,301	-0,078	0,061	SEC ISSUED to TA					
0,011	0,101	0,015	-0,028	0,558	0,100	0,184	-0,090	0,078	0,141	-0,137	0,702	0,201	0,311	-0,487	-0,251	-0,330	-0,065	-0,234	0,010	0,004	0,079	SEC HELD to TA				

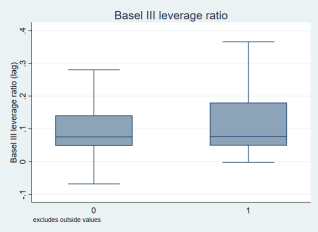
Matrix of correlations between variables used in the regressions - Cooperative banks

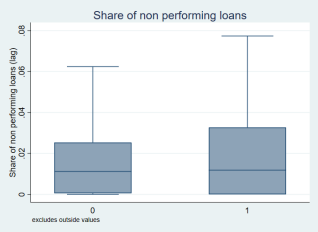
The gradient of colors from blue to red respectively indicates highest negative / positive correlations.

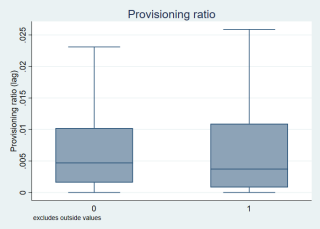
For each CAMELS category and controls, variables are sorted by decreasing absolute value of correlation coefficient with the "Distress" variable.

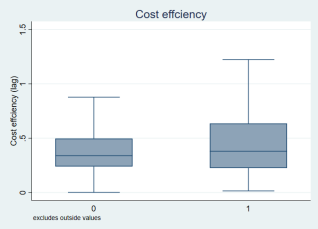
Appendix 2 - Box plots of lagged explanatory variables

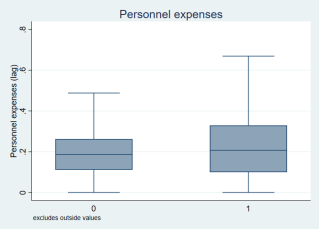


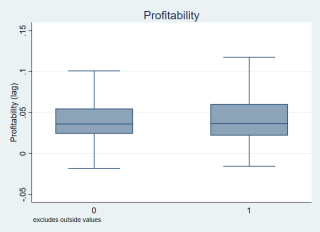


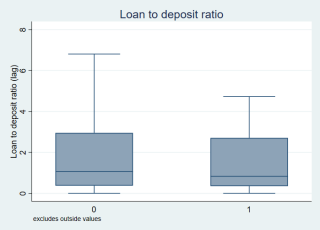


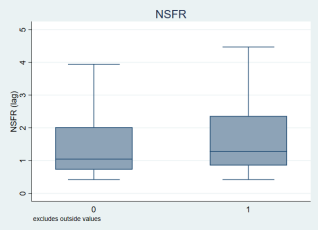


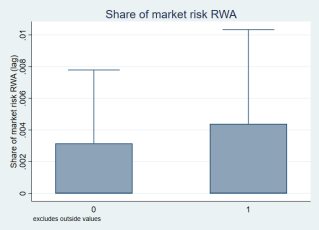


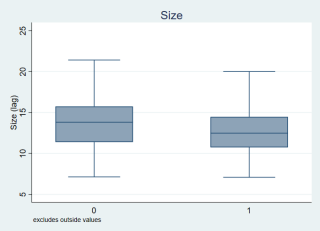


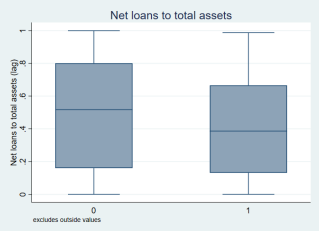


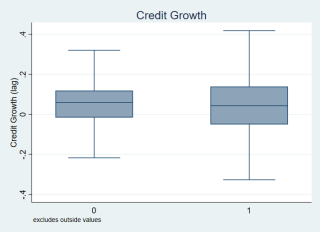


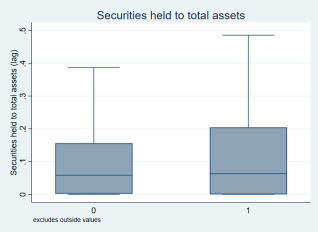


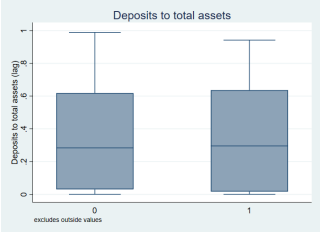


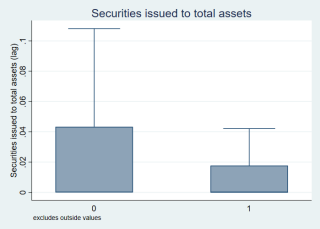


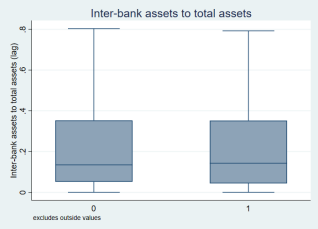


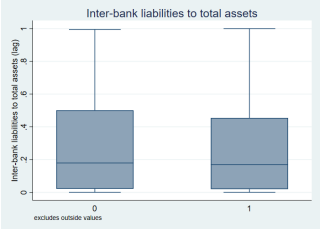

Credit Growth
Credit Growth (lag)
-.4
-.2
0
.2
.4
0
1
excludes outside values

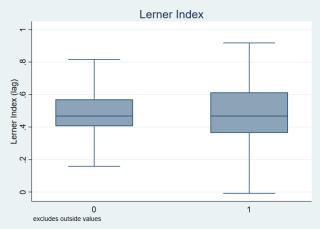

Securities held to total assets
Securities held to total assets (lag)
0
.1
.2
.3
.4
.5
0
1
excludes outside values


Deposits to total assets
Deposits to total assets (lag)
0
.2
.4
.6
.8
1
0
1
excludes outside values


Securities issued to total assets
Securities issued to total assets (lag)
0
.02
.04
.06
.08
.1
0
1
excludes outside values

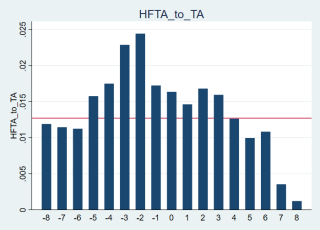

Inter-bank assets to total assets
Inter-bank assets to total assets (lag)
0
.2
.4
.6
.8
0
1
excludes outside values

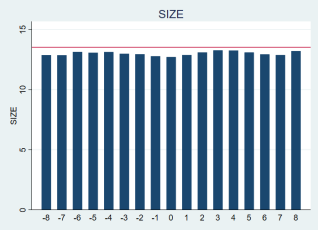

Inter-bank liabilities to total assets
Inter-bank liabilities to total assets (lag)
0
.2
.4
.6
.8
1
0
1
excludes outside values

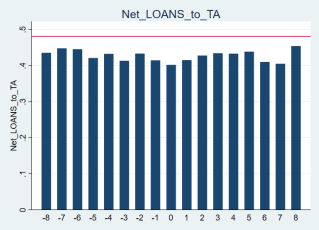

Lerner Index
Lerner Index (lag)
0
.2
.4
.6
.8
1
0
1
excludes outside values

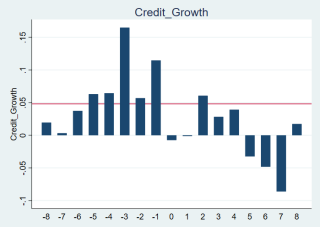
Appendix 3 - Evolution of variables before and after distress at t=0

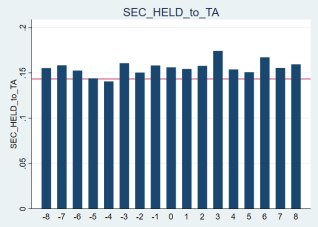
In the graphs below, vertical blue bars represent the average level of the variable for distressed banks from 8 years before distress occurs at t=0 to 8 years after. The red horizontal line indicates the average level of the variable for all non-distressed banks over the full time period covered by the dataset (ie. 1997-2013).

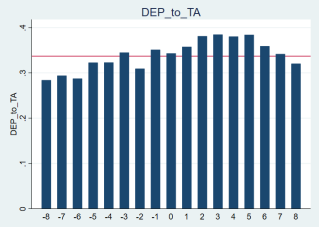

HFTA_to_TA
HFTA_to_TA
0
.005
.01
.015
.02
.025
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8

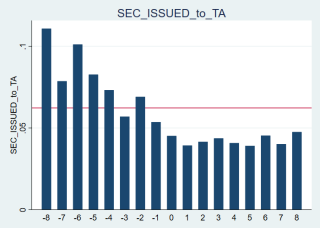

SIZE
SIZE
0
5
10
15
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8

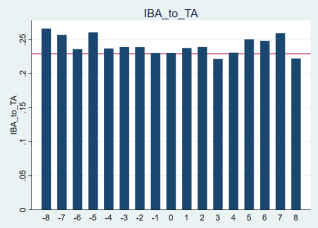

Net_LOANS_to_TA
Net_LOANS_to_TA
0
.1
.2
.3
.4
.5
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8

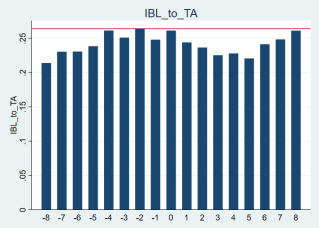

Credit_Growth
Credit_Growth
-.1
-.05
0
.05
.1
.15
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8

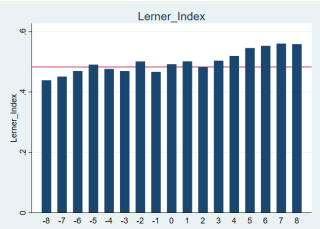

SEC_HELD_to_TA
SEC_HELD_to_TA
0
.05
.1
.15
.2
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8


DEP_to_TA
DEP_to_TA
0
.1
.2
.3
.4
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8


SEC_ISSUED_to_TA
SEC_ISSUED_to_TA
0
.05
.1
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8


IBA_to_TA
IBA_to_TA
0
.05
.1
.15
.2
.25
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8


IBL_to_TA
IBL_to_TA
0
.05
.1
.15
.2
.25
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8


Lerner_Index
Lerner_Index
0
.2
.4
.6
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8

Appendix 4 - Computing banks' Lerner Index

Following Weill [2013], we compute a Lerner Index for each bank at yearly frequency in order to get a measure of the market power of the bank and then take into account the effect of competition into our main regressions. The Lerner Index is defined as the following ratio: $\frac{price - marginal\ cost}{price}$. Under perfect competition, the price would equal the marginal cost and then the Lerner Index would be zero. On the other hand, the higher the market power of the bank, the higher the mark-up. So a larger Lerner Index reveals a stronger market power of the bank. As usual in the literature (see for instance Fernandez de Guevara et al. [2005] and Carbo et al. [2009]), the *price* is estimated as the ratio of total revenues to total assets. The estimation of the marginal cost is more complex and requires an estimation of the total cost function of the bank with one output (total assets - TA) and three inputs: labor, physical capital, and borrowed funds. Total cost (TC) of a bank is the sum of the costs generated by these three inputs, respectively: total personnel expenses, other non-interest expenses and interest expenses. The prices of these three inputs are then derived as follows: $w_1 = \frac{Personnel\ expenses}{Total\ assets}$, $w_2 = \frac{other\ non-interest\ expenses}{Fixed\ assets}$ and $w_3 = \frac{Interest\ expenses}{Funding}$. Using these parameters, we can estimate the following equation:

$$ln(TC) = \alpha_0 + \alpha_1.ln(TA) + \frac{1}{2}.\alpha_2.ln(TA)^2 + \sum_{i=1}^{3}\beta_i.ln(w_i)$$
$$+ \sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk}.ln(w_j).ln(w_k) + \sum_{i=1}^{3}\gamma_i.ln(TA).ln(w_i) + \epsilon$$

The table below displays the result of this regression. Finally, the *marginal cost* (MC) is derived as follows by differentiating previous equation with respect to $ln(TA)$:

$$MC = \frac{TC}{TA}.\left(\alpha_1 + \alpha_2.ln(TA) + \sum_{i=1}^{3}\gamma_i.ln(w_i)\right)$$

	Dependent variable: $ln(TC)$
$ln(TA)$	1.048***
	(0.050)
$1/2.ln(TA)^2$	0.022***
	(0.008)
$ln(w_1)$	-0.123***
	(0.037)
$ln(w_2)$	0.238***
	(0.029)
$ln(w_3)$	-0.074**
	(0.030)
$ln(w_1).ln(w_1)$	0.003**
	(0.001)
$ln(w_1).ln(w_2)$	0.001
	(0.003)
$ln(w_1).ln(w_3)$	-0.015***
	(0.004)
$ln(w_2).ln(w_1)$	(omitted)
$ln(w_2).ln(w_2)$	-0.011***
	(0.002)
$ln(w_2).ln(w_3)$	-0.054***
	(0.003)
$ln(w_3).ln(w_1)$	(omitted)
$ln(w_3).ln(w_2)$	(omitted)
$ln(w_3).ln(w_3)$	0.039***
	(0.001)
$ln(TA).ln(w_1)$	0.016***
	(0.005)
$ln(TA).ln(w_2)$	-0.027***
	(0.004)
$ln(TA).ln(w_3)$	0.041***
	(0.004)
Intercept	-2.868***
	(0.247)

Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations in brackets.

Table 21: Estimating total cost function for Lerner Index

Appendix 5 - Precisions about regression (7) of table 6

This appendix provides additional details about regression (7) displayed in table 6. This regression applies a stepwise approach on the set of explanatory and control variables. The table below shows the variables selected by the stepwise procedure, the order in which they entered the regression, and the improvement they bring to the area under ROC curve.

Order	Variable name	Cumulative area under ROC curve	Improvement of area under ROC curve
0	—	0.5000	—
1	SIZE (lag)	0.6162	+0.1162
2	ROA (lag)	0.6488	+0.0326
3	Unemployment (lag)	0.6507	+0.0019
4	HFTA to TA (lag)	0.6572	+0.0064
5	Volatility of ROA (lag)	0.6560	-0.0011
6	LR B3 (lag)	0.6644	+0.0084
7	ST Interest Rate (lag)	0.6658	+0.0013
8	Net LOANS to TA (lag)	0.6708	+0.0049
9	PROV to TA (lag)	0.6773	+0.0065
10	IBA to TA (lag)	0.6834	+0.0060
11	NSFR (lag)	0.6906	+0.0072

Chapter 2.

The Impact of the Designation of Global Systemically Important Banks on Their Business Model

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The Impact of the Designation of Global Systemically Important Banks on Their Business Model*

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To the best of our knowledge, this paper is among the first to provide empirical evidence on how the recent international regulation designed for global systemically important banks (G-SIBs) drove changes in these institutions' activity. Our econometric approach quantifies the impact of the designation of G-SIBs on their activity, controlling for both structural differences and industry trends. We find that G-SIBs have reduced the expansion of their balance sheet, which further improved their leverage ratio. A downward pressure is noticed on their return on equity, but no adverse consequences are observed on lending. We find no effect on G-SIBs' funding cost advantage, which suggests that "too-big-to-fail" distortions still persist.

JEL Codes: G01, G21, G28, G32.

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1. Introduction

At the Pittsburgh Summit in 2009, G-20 leaders called on international regulators to propose solutions to the "too-big-to-fail" (TBTF) problem (Financial Stability Board 2010). Whereas this category of banks had already been identified in 1984[1] and the adverse incentives related to their status had largely been analyzed by academics (Flannery and Sorescu 1996; Freixas, Rochet, and Parigi 2004; Brandao-Marques, Correa, and Sapriza 2013; Gropp, Gruendl, and Guettler 2013), no concrete measure had been taken until the crisis had burst in order to end the TBTF distortions. The 2008 financial crisis clearly revealed that size is only one determinant of systemic risk; the complexity of a bank's business model, its interconnections with other financial entities, and internationally driven activities are other key dimensions of systemic risk.

Thus, the quantification of banks' systemic footprint and the identification of "the financial institutions whose distress or disorderly failure could cause significant disruption to the wider financial system and to the economic activity" (Financial Stability Board 2011) became a priority for international regulators and a key element of the post-Lehman reform agenda. Several measures of the systemic footprint of large banks have been developed in the academic literature, mainly based on market data, and they are still subject to ongoing discussions and refinements: the marginal expected shortfall and the systemic expected shortfall of Acharya et al. (2017), the SRISK of Acharya, Engle, and Richardson (2012) and Engle, Jondeau, and Rockinger (2015), and the CoVaR of Adrian and Brunnermeier (2016).[2] In parallel, using mainly accounting and prudential information, international regulators developed specific frameworks to make large financial institutions more resilient and to bring an end to the "too-big-to-fail" paradigm (Financial Stability Board 2010, 2013a).

[1] In 1984, the U.S. federal government made the decision to intervene in order to avoid the failure of any of the nation's 11 largest banks. This led to the identification of a new category of banks, whose disorderly failure, due to their size, could cause significant disruption in the functioning of financial markets and the economy as a whole.

[2] Benoit et al. (2017) provides a comparative analysis of these systemic risk indicators.

To that end, the concept of a "global systemically important bank" (G-SIB) has been introduced to characterize banks to be submitted to more stringent regulatory, supervisory, and resolution regimes. The publication of the first list of G-SIBs by the Financial Stability Board (FSB) occurred in November 2011. This approach further facilitated a focused implementation of additional capital requirements (additional capital buffers, higher loss-absorbency requirements imposed under the total loss-absorbing capacity, or TLAC, framework), macroprudential measures, and additional recovery and resolution regulation (FSB 2013a, 2014a, 2015a, 2016a). The rollout of the framework has taken place progressively and will continue in the coming years.[3]

In this context, this paper seeks to evaluate whether the regulatory reforms for systemic banks have contributed to the G-20 objectives to strengthen the resilience of financial institutions and enhance global financial stability. More precisely, we will evaluate whether and how much banks designated as G-SIBs have experienced changes in line with the intended objectives, and if some unintended consequences also occurred.

Research efforts have been driven so far to investigate the effects of G-SIB regulation, but usually from a different point of view: the impact of G-SIB designation on banks' debt implicit public guarantees and the efficiency of resolution regimes and practices (Schich and Toader 2017), or the shifts in stock market evaluations driven by the recent regulatory frameworks imposed on G-SIBs (Moenninghoff, Ongena, and Wieandt 2015), or the calibration of optimal capital requirements (Passmore and von Hafften 2017). Birn, Dietsch, and Durant (2017) investigate with a nonlinear optimization model how Basel III capital and liquidity requirements combine and result in a changing balance sheet.[4] They suggest that G-SIBs, contrary to their peers, have decreased total balance sheet and simultaneously increased more than other banks the share of highly liquid instruments required to fulfill the liquidity coverage ratio (LCR). To the

[3]Additional prudential requirements were phased in from January 1, 2016 to January 1, 2019. TLAC requirements have to be fulfilled by 2022.

[4]The empirical part of this study is based on bank-level data from the Basel Committee on Banking Supervision's (BCBS's) quantitative impact studies for 156 banks between 2011 and 2014.

best of our knowledge, almost no empirical analysis on the structural changes in G-SIBs' business models has been published so far,[5] thus our paper intends to fill this gap in the literature.

In this study, we empirically assess whether the post-crisis regulations specifically applied to G-SIBs, starting with their first designation by the FSB in 2011, have driven changes in their business models, broadly speaking. We first investigate whether the size and structure of the balance sheet has evolved in response to the new regulatory reforms, and we focus on the effects on the traditional activity of lending. Then, we evaluate changes in the risk-taking behavior and the cost of funding, to ultimately assess regulatory driven variations in overall profitability. In order to deal with such questions, we use granular balance sheet and income statement data from a sample of 97 large banks over a 12-year period between 2005 and 2016. Using this database, we apply an econometric approach inspired by the "difference-in-difference" methodology. We show that some key objectives of the BCBS have been achieved, namely we identify a major reduction of the balance sheet expansion of G-SIBs and a return to the mean in terms of financial leverage. However, it appears that the funding advantage derived by G-SIBs from the implicit public guarantees persists, which indicates that the "too-big-to-fail" status has not totally been put to an end.

The remaining of this paper proceeds as follows. Section 2 presents an overview of the post-crisis reforms dedicated to G-SIBs. In sections 3 and 4 we describe the data set and the methodology that allows us to analyze empirically our topic of interest. In section 5, we present the econometric results focusing on different aspects of banks' business model (balance sheet patterns, risk-taking, cost of funding, and profitability). Section 6 elaborates on the robustness of these results and section 7 concludes.

2. Overview of Post-Crisis Reforms for G-SIBs

The G-20 post-crisis agenda dealt with the systemic and moral hazard risks associated with systemically important financial

[5]See BCBS (2019) for a recent analysis of the trends of the indicators used in the BCBS methodology.

institutions (SIFIs)[6] with the aim to build a more resilient financial system. Almost 10 years after the G-20 leaders called on the FSB to propose possible measures to address the too-big-to-fail distortions generated by SIFIs, the need for concrete evidence on the contribution of the G-20 reforms in building a more resilient financial system is mandatory for the legitimacy and the credibility of FSB's post-crisis reform agenda.

Following the G-20 mandate given to the FSB in 2009, the concept of a G-SIB has been introduced to characterize the banks to be subject to new additional regulations. In November 2011, the BCBS published a methodology designed to identify these systemically important institutions focusing on five main features: size, interconnectedness, substitutability, global activity, and complexity (FSB 2011; BCBS 2011). Based on a score analysis, a first list of 29 G-SIBs (17 from Europe, 8 from the United States, and 4 from Asia) was published by the FSB in November 2011. Ever since, this list is updated and published annually each November on the FSB website.[7] This identification methodology went through several changes since its creation, particularly in November 2012 when it was revised to allocate G-SIBs into five *"buckets"* of ascending levels of systemic importance (FSB 2013a, 2014a, 2015a).[8] The latest version of the BCBS methodology was disclosed in July 2013 (BCBS 2013a).[9] Appendix B provides a broad description of this methodology developed by the BCBS for the identification of G-SIBs.

The designation of G-SIBs and their allocation into buckets were primarily conceived to enforce gradual additional capital requirements. Initially, only risk-based capital buffers were required, staging from 1 percent to 3.5 percent. More recently, in 2017, a corresponding additional buffer for the leverage ratio requirement of G-SIBs

[6]FSB (2011).

[7]http://www.fsb.org/work-of-the-fsb/policy-development/systematically-important-financial-institutions-sifis/global-systemically-important-financial-institutions-g-sifis/. For annual updates used for this paper, please see FSB (2012, 2013b, 2014b, 2015b, and 2016b).

[8]Benoit, Hurlin, and Pérignon (2019) question the adequacy of the current BCBS's methodology. They propose a correction of the score methodology and an alternative list of systemically important institutions to be further used to set capital surcharges or alternative tax on systemic risk.

[9]Available online at https://www.bis.org/publ/bcbs255.htm.

was also introduced. However, such additional capital buffers are only one aspect of the direct consequences of being designated as a G-SIB. Indeed, G-SIBs are also subject to a minimum TLAC requirement ensuring that in case of resolution the bank holds enough instruments to absorb losses and to be recapitalized without public funds intervention (cf. FSB 2014a). Other consequences of the G-SIB designation also have to be taken into account: for instance, cross-border supervisory colleges are put in place for almost all G-SIBs in order to enhance international supervisory cooperation, and G-SIBs are subject to further resolution planning expectations from authorities. G-SIBs are also requested to take part into additional reporting and statistical data collections, such as the FSB Datagaps initiative that imposes a weekly submission of their main exposures and a monthly submission of their top financing sources. Finally, the annual publication of the list of G-SIBs by the FSB is supposed to draw investors' attention on this particular set of banks, so a specific "market discipline" is supposed to affect them. Hence, for the remainder of this paper, it is crucial to have in mind that what we call *the impact of the G-SIB designation* actually covers this complete set of consequences that applies to G-SIBs, and not only the sole capital buffer.

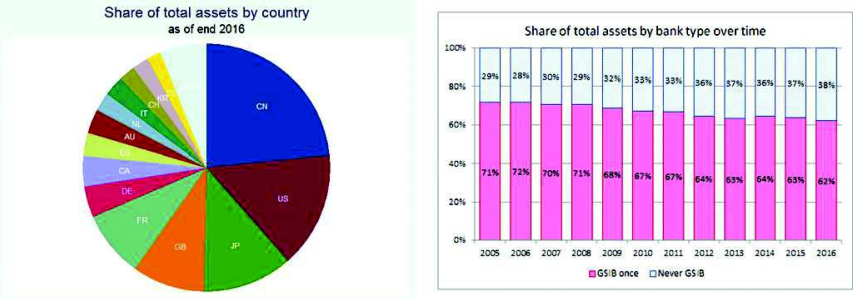
The constraints resulting from being a G-SIB were staged through time, with a leeway for G-SIBs to anticipate or delay the change in balance sheet until the effective implementation date. Additionally, the phasing-in of Basel III may have affected G-SIBs differently from other banks due to their structure of activity.[10] It is thus not possible to precisely define a clear cutoff date where the G-SIB constraint would apply.

3. Data Set Description

We exploit balance sheet and income statement data for 97 large banks from 22 countries over the period from 2005 to 2016 (12 years). We focus on a sample of large banks with total assets exceeding 200

[10]For example, Birn, Dietsch, and Durant (2017) demonstrate that G-SIBs have suffered more than other banks from the treatment of derivatives and short-term loans that was made more stringent for the net stable funding ratio (NSFR).

Figure 1. Shares of Total Assets by National Banking System (left) and by Type of Bank (right)



billion euros[11] as of end-2016, at the highest level of consolidation (subsidiaries are excluded). A detailed list of banks considered in the study is provided in appendix A. The distribution of national banking systems into the aggregated total assets is shown in the left panel of figure 1 (for color versions of the figures, see http://www.ijcb.org). The right panel of figure 1 shows that the share of total assets held by banks that have been designated as G-SIB at least once by the FSB between 2011 and 2016[12] is decreasing over time within our sample.

For each bank, we collected a set of variables at yearly frequency[13] using the S&P Global Market Intelligence database.[14] Table 1 provides a description of the variables that we use as successive dependent variables in the regressions.[15]

[11]This cutoff is inspired by the €200 billion threshold in terms of Basel III leverage ratio exposure which is used by the BCBS to identify its sample. There are usually around 75 banks in this BCBS sample. The difference with our sample of 97 banks mostly comes from the different measures used (total assets versus leverage exposure) for several banks whose size is close to the €200 billion threshold. We chose total assets, as the leverage ratio exposure measure was not fully available over the period.

[12]They are listed in appendix A.

[13]Most series were not available at higher frequency (half-yearly or quarterly) for many banks. Moving to such higher frequency would therefore drastically reduce the number of banks in the sample.

[14]This was previously known as the "SNL Financial" database.

[15]Note that in order to avoid potential disturbance of our results by extreme outliers, some variables are winsorized at the 1st and 99th percentiles. This means that, for a given variable, any value larger than the 99th percentile will actually be capped at this level. Similarly, any value lower than the 1st percentile will be raised up to this level. Also note that, in order to ensure the stationarity of our series, which is required from an econometric technical perspective, all variables are expressed either as scaled by an aggregate (e.g., total assets), as ratios, or as growth rates.

Table 1. List of Dependent Variables

Variable Code	Variable Description	Obs.	Mean	Std. Dev.	Min.	Max.
Balance Sheet and Prudential Ratios						
TA gr	Total Assets (TA) Growth Rate	1,023	8.94%	13.34%	−21.01%	65.03%
TA/GDP	Total Assets over GDP	1,083	38.28%	41.61%	1.07%	206.96%
T1 gr	Tier 1 Capital (T1) Growth Rate	886	13.94%	21.75%	−25.4%	119.75%
T1/TA	Tier 1 Capital over Total Assets ("Leverage Ratio")	990	5.09%	1.81%	1.23%	10.22%
T1/RWA	Tier 1 Capital over RWA (Solvency Ratio)	972	11.72%	4.51%	4.9%	37.87%
CASH CB/TA	Cash and Balances with Central Banks over TA	681	5.97%	5.19%	0.11%	22.12%
CUST LOANS/TA	Net Customer Loans over TA	681	51.61%	14.95%	2.11%	82.05%
SUB DEBT/TL	Total Subordinated Debt over Total Liabilities	679	1.84%	1.13%	0%	6%
Profitability, Risk-Taking, and Yield Ratios						
NET PROF/OP INC	Net Profit over Op. Inc.	663	23.99%	44.36%	−513.49%	424.54%
ROA	Return on Average Assets	1,037	0.66%	0.53%	−0.87%	2.24%
ROE	Return on Average Equity	1,017	10.5%	9.08%	−24.6%	30.33%
NPL/LOANS	Share of NPL over Total Loans	1,003	2.73%	2.96%	0%	15.94%
RWA Density	Total RWA over Total Assets	1,000	47.4%	17.88%	6.77%	87.9%
LOAN YIELD	Total Loans Yield	686	5.22%	3.15%	0.58%	18.5%
DEP COST	Total Deposits Interest Cost	686	2%	1.66%	0.05%	8.4%
NIM	Net Interest Margin	686	2.16%	1.33%	0.09%	6.76%

In a first set of dependent variables, we focus on some key indicators of balance sheet and prudential ratios. Our first variables of interest are the yearly growth rates of total assets and tier 1 capital, as well as the size of banks relative to their national economy measured by gross domestic product (GDP). We also include two capital adequacy ratios: a nonweighted ratio dividing tier 1 capital (T1) by total assets (TA), which is a proxy of the leverage ratio (hereafter referred to as "leverage ratio"[16]) and a weighted solvency ratio dividing T1 capital by total risk-weighted assets (RWA). Finally, we have three indicators for the composition of the balance sheet: the share of cash (and balances with central banks) within total assets, the share of loans to nonfinancial customers within total assets, and the share of subordinated debt within total liabilities.

In a second set of dependent variables, we focus on profitability measures, risk-taking indicators, and yield rates. We include in this set of variables the ratio of net profit over the operating income, the return on assets (ROA), and the return on equity (ROE). In order to capture the risk-taking behavior of banks, we use the RWA density (i.e., total RWA over total assets), which corresponds to the average risk weight of the balance sheet, and we also compute the nonperforming loans (NPL) ratio as a measure of asset quality. We also investigate the loan yield, the average cost of deposits, and the net interest margin.

Table 2 displays some summary statistics for these dependent variables and details the means for G-SIBs and non–G-SIBs over the two periods (2005–11 and 2012–16). Figures 2 and 3 illustrate the evolution over time of the average of these variables of interest for G-SIBs versus non–G-SIBs. These figures and table 2 provide preliminary indications about some general trends that will further be confirmed econometrically in section 5. For instance, we notice a drastic reduction of the growth rate of total assets and of the return on equity for G-SIBs, compared with non–G-SIBs, during the second period. They also highlight a structurally lower leverage ratio for G-SIBs, but the gap compared with non–G-SIBs tended to shrink over time.

[16]It differs from the regulatory definition of the Basel III leverage ratio, which was not fully available over the period.

Table 2. Means by Subgroup and Subperiod

Variables	All Banks			G-SIB (At Least Once)		Never G-SIB			
	Mean 2005–11 (A)	Mean 2012–16 (B)	T-test (B) – (A) t-stat	Mean 2005–11 (C)	Mean 2012–16 (D)	Mean 2005–11 (E)	Mean 2012–16 (F)	T-test (E) – (C) t-stat	T-test (F) – (D) t-stat
Balance Sheet and Prudential Ratios									
TA gr	11.8%	5.71%	−7.489***	10.32%	0.48%	12.62%	8.49%	1.78**	7.977***
	Obs = 542	*Obs = 481*		*Obs = 193*	*Obs = 167*	*Obs = 349*	*Obs = 314*		
TA/GDP	38.97%	37.43%	−0.607	58.14%	52.07%	28.27%	29.62%	−8.258***	−6.574***
	Obs = 600	*Obs = 483*		*Obs = 215*	*Obs = 168*	*Obs = 385*	*Obs = 315*		
T1 gr	17.87%	9.59%	−5.761***	14.98%	5.68%	19.54%	11.48%	1.86**	3.646***
	Obs = 465	*Obs = 421*		*Obs = 170*	*Obs = 137*	*Obs = 295*	*Obs = 284*		
T1/TA	4.72%	5.56%	7.393***	4.33%	5.31%	4.94%	5.68%	3.851***	2.097**
	Obs = 556	*Obs = 434*		*Obs = 201*	*Obs = 143*	*Obs = 355*	*Obs = 291*		
T1/RWA	10.15%	13.74%	13.356***	10.15%	14.1%	10.15%	13.55%	−0.018	−1.159
	Obs = 548	*Obs = 424*		*Obs = 201*	*Obs = 143*	*Obs = 347*	*Obs = 281*		
CASH	5.4%	6.6%	4.687***	4.2%	7.33%	6.08%	6.2%	3.092***	−2.13**
CB/TA	*Obs = 356*	*Obs = 325*		*Obs = 129*	*Obs = 116*	*Obs = 227*	*Obs = 209*		
LOANS	51.84%	51.37%	−0.417	43.6%	43.4%	56.52%	55.79%	8.209***	8.233***
CUST/TA	*Obs = 356*	*Obs = 325*		*Obs = 129*	*Obs = 116*	*Obs = 227*	*Obs = 209*		
SUB	1.94%	1.73%	−6.059***	1.93%	1.73%	1.94%	1.73%	0.044	0.007
DEBT/TL	*Obs = 372*	*Obs = 307*		*Obs = 142*	*Obs = 116*	*Obs = 230*	*Obs = 191*		

(*continued*)

Table 2. (Continued)

Variables	All Banks			G-SIB (At Least Once)		Never G-SIB			
	Mean 2005–11 (A)	**Mean 2012–16 (B)**	**T-test (B) – (A) t-stat**	**Mean 2005–11 (C)**	**Mean 2012–16 (D)**	**Mean 2005–11 (E)**	**Mean 2012–16 (F)**	**T-test (E) – (C) t-stat**	**T-test (F) – (D) t-stat**
Profitability, Risk-Taking, and Yield Ratios									
NET PROF/ OP INC	21.09% *Obs = 367*	27.59% *Obs = 296*	2.178**	17.07% *Obs = 134*	24.72% *Obs = 94*	23.4% *Obs = 233*	28.93% *Obs = 202*	1.17	0.932
ROA	0.69% *Obs = 556*	0.63% *Obs = 481*	−1.635	0.59% *Obs = 202*	0.46% *Obs = 167*	0.74% *Obs = 354*	0.72% *Obs = 314*	3.201***	5.588***
ROE	11.52% *Obs = 536*	9.37% *Obs = 481*	−3.8***	9.9% *Obs = 189*	6.08% *Obs = 167*	12.4% *Obs = 347*	11.12% *Obs = 314*	2.816***	6.948***
RWA Density	49.09% *Obs = 551*	45.33% *Obs = 449*	−3.326***	44.07% *Obs = 201*	41.45% *Obs = 159*	51.97% *Obs = 350*	47.45% *Obs = 290*	5.237***	3.38***
NPL/LOANS	2.65% *Obs = 540*	2.83% *Obs = 463*	0.941	3.25% *Obs = 199*	3.12% *Obs = 161*	2.3% *Obs = 341*	2.67% *Obs = 302*	−3.922***	−1.431***
LOAN YIELD	5.57% *Obs = 362*	4.83% *Obs = 324*	−3.316***	4.7% *Obs = 113*	3.5% *Obs = 93*	5.96% *Obs = 249*	5.36% *Obs = 231*	4.036***	4.534***
DEP COST	2.25% *Obs = 362*	1.72% *Obs = 324*	−5.812***	1.76% *Obs = 113*	0.92% *Obs = 93*	2.47% *Obs = 249*	2.04% *Obs = 231*	4.065***	5.538***
NIM	2.25% *Obs = 362*	2.05% *Obs = 324*	−2.381***	1.88% *Obs = 113*	1.51% *Obs = 93*	2.42% *Obs = 249*	2.26% *Obs = 231*	3.674***	4.749***

Note: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 2. Evolution of the Average Balance Sheet and Prudential Ratios for G-SIBs (red/lighter bars) versus Non–G-SIBs (blue/darker bars)

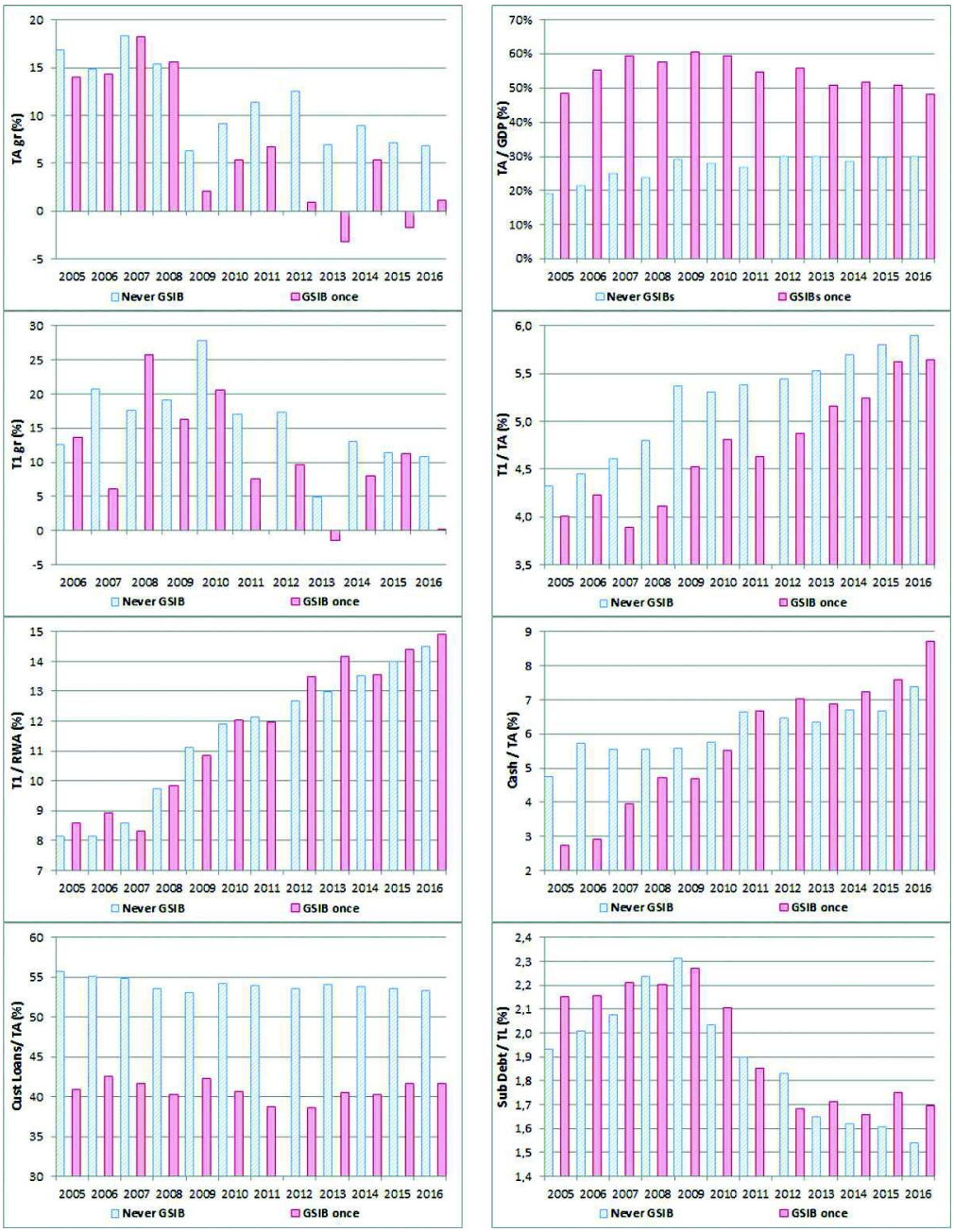
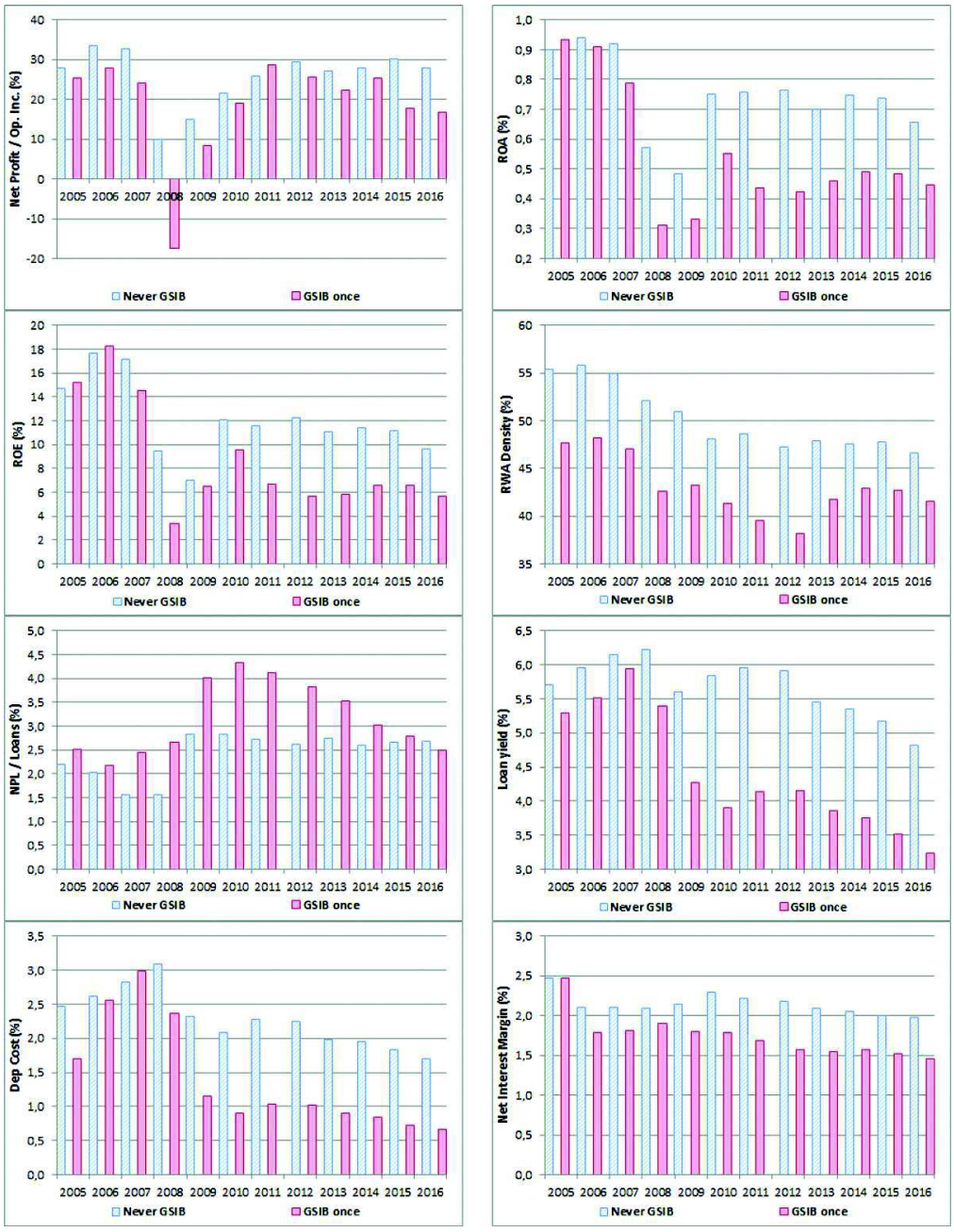


Figure 3. Evolution of the Average Profitability, Risk-Taking, and Yield Ratios for G-SIBs (red/lighter bars) versus Non–G-SIBs (blue/darker bars)



4. Econometric Methodology

4.1 Specification

This paper seeks to evaluate the changes that affected G-SIBs following the announcement and/or implementation of the prudential

rules dedicated to this specific category of banks. With such objective in mind, we rely on an approach inspired by the difference-in-difference methodology.[17] In a standard difference-in-difference model, the group of G-SIBs would correspond to the *treated* group while the group of other banks (here "non–G-SIBs") would constitute the *control* group. We compare the post-crisis reform-driven evolutions of business models' characteristics for these two groups of banks.

As the list of G-SIBs is relatively stable (with only a few entries and exits each year, if any),[18] we will consider as a G-SIB every bank that has been designated at least once by the FSB between 2011 and 2016. Hence we construct the $GSIB_{i,k}$ binary variable that takes value 1 for all periods t if the G-SIB i located in country k appeared on the FSB list at least once between 2011 and 2016, and 0 otherwise. Regarding the time dimension, even if it is not possible to precisely define a clear cutoff date where the G-SIB constraint would apply (due to the phased-in approach of the regulation, as discussed in section 2), we should recall that the first list of banks designated as G-SIBs was disclosed by the FSB in November 2011. Hence, we construct a binary variable $Post2011_t$ that equals 1 if $t > 2011$ and 0 otherwise. Note that, contrary to "event studies" papers, we do not rely on this precise cutoff date, as we do not claim that G-SIBs reforms had an effect on a very precise and short timing, but instead had a gradual effect over time. Section 6 provides some robustness checks testing alternative definitions of the $GSIB_{i,k}$ and $Post2011_t$ variables. Contrary to "placebo tests" usually performed in event studies, the fact that results remain stable for alternative cutoff date shows that the "arbitrary" decisions made for these two binary variables here are not driving the results.

In addition to these two main explanatory variables, a set of bank-specific time-varying control variables and some country-specific time-varying factors are considered. At the end, we select a given dependent variable Y (among those listed in table 1) for all

[17]We use a similar approach to the one developed by Grill, Lang, and Smith (2018), Hills et al. (2017), and especially Schich and Toader (2017), applied to different regulatory contexts.

[18]These rare changes of the list of G-SIBs might be used for other analyses, such as case studies, but this is not the purpose of this paper and this is left for future research.

banks i, incorporated in country k at time t, and we regress it on the two binary variables described above, $GSIB_{i,k}$ and $Post2011_t$, and on the cross-variable *interaction term* of these two variables: $(GSIB_{i,k} \times Post2011_t)$, as well as on control variables. We estimate the following model[19]:

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t) + \varphi B_{i,k,t} + \chi C_{k,t} + PTH_t + u_{i,k,t}, \quad (1)$$

with $B_{i,k,t}$ being the set of bank-specific control variables, $C_{k,t}$ the set of country-specific macroeconomic control variables, PTH_t a conditional time-dummy variable capturing potential violations of the "parallel trend hypothesis,"[20] and $u_{i,k,t}$ being an error term. Since we cannot be sure that observations are iid among banks, standard errors will be clustered at individual level in all our regressions.

The set of country-specific macroeconomic control variables $C_{k,t}$, described in table 3, will be included in all following regressions to take into account potential structural discrepancies between economies in terms of growth, wealth, unemployment, inflation, public debt, aggregate credit growth, and sovereign yield. These variables can also capture specific conditions of the macroeconomic environment in some countries, such as the sovereign debt crisis in Europe.[21] The annual growth rate of exchange rate against the euro is also included since our data set in entirely denominated in euros, for consistency reasons. The set of bank-specific control variables $B_{i,k,t}$ included in the regressions can vary from one dependent variable to another and will be described below each regression table in the next section.

The econometric identification strategy described in equation (1) allows us to assess the impact of the G-SIB designation on their

[19]Section 6 also provides some robustness checks of this model, testing alternative specifications.

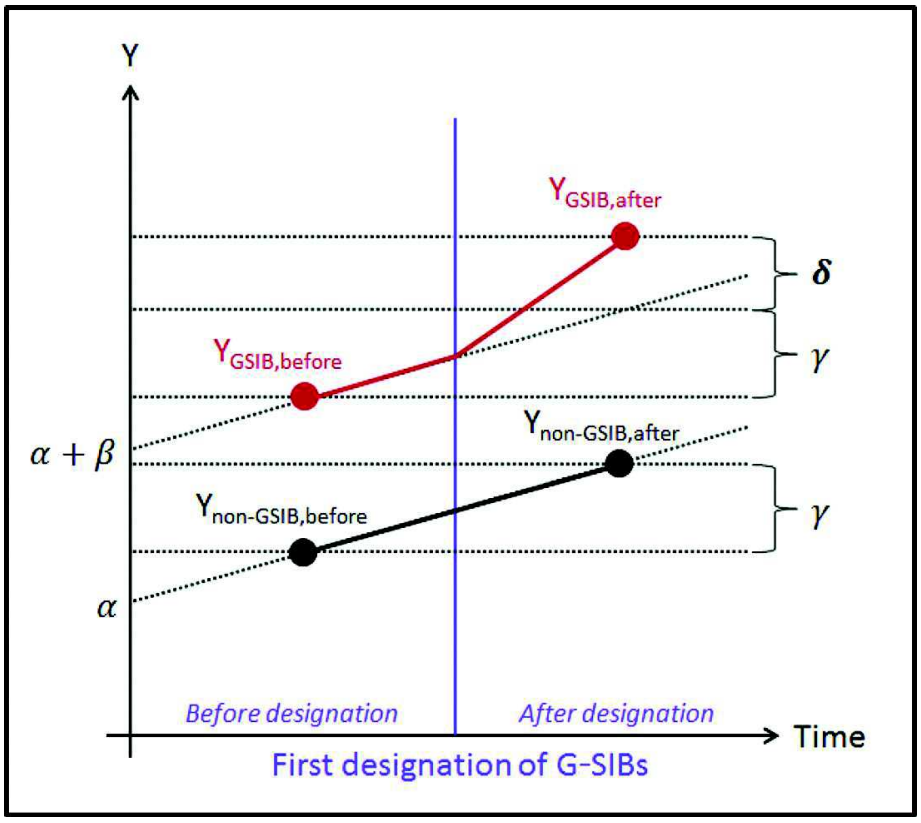
[20]See the explanation below in section 4.2.

[21]As an additional robustness check, we also include the 10-year government CDS spreads in order to capture the impact of the sovereign debt crisis that affected some countries. These results are presented in column "Gov. CDS Spread" of table 8.

Table 3. Set of Country-Specific Macroeconomic Control Variables $C_{k,t}$

Variable Code	Variable Description	Obs.	Mean	Std. Dev.	Min.	Max.
GDP gr	Real GDP Growth (%)	1,164	3.03%	3.72%	−7.93%	15.24%
GDPperCap	GDP per Capita (USD/Year)	1,164	35,943	19,160	714	102,723
UR	Unemployment Rate (%)	1,164	6.12%	3.18%	1.9%	26.09%
INPL	Inflation (%)	1,164	2.13%	1.96%	−1.35%	15.52%
PUBD/GDP	Public Debt/GDP (%)	1,164	67.17%	48.30%	4.95%	222.23%
DOMCRED gr	Domestic Credit Growth (%)	1,164	7.97%	8.23%	−15.07%	40.63%
SOVYIELD	10-Year Sovereign Debt Yield (%)	1,164	3.38%	2.47%	−0.14%	16.49%
FXRATE gr	Annual Growth Rate of Exchange Rate against Euro (%)	1,164	−0.60%	9.53%	−25.27%	59.6%

Figure 4. Illustration of the Econometric Methodology in the Univariate Case



structural patterns. It is applied successively to each of our dependent variables listed in table 1. Within this framework, our main parameter of interest will be δ, the coefficient of the interaction term. It captures the causal impact of the designation by the FSB on the Y variable for G-SIBs, controlling for both the effect of structural differences between G-SIBs and non–G-SIBs (captured by the coefficient β of the binary variable $GSIB_{i,k}$), and the time structural changes, or "industry trends" (captured by the coefficient γ of the variable $Post2011_t$). The graphic illustration in figure 4 gives a visual illustration of this approach in a simple univariate case.

However, it is recognized that this econometric identification has some limitations. The model is able to take into account general evolutions of the environment, both macroeconomic conditions and implementation of new regulations affecting the whole banking system. This is the purpose of using two subgroups and two subperiods that should be affected in a similar way by these general evolutions,

while only G-SIBs are affected by the designation. On the other hand, it will not be able to disentangle the effects of each individual consequence of the designation of a bank as a G-SIB by the FSB. As described in section 2, such designation entails several regulatory implications, such as capital buffers and TLAC requirements. Therefore, one should keep in mind that the estimator δ captures the *overall* effect of all diverse consequences posterior to the G-SIB designation, and not the impact of the sole additional capital requirement.

4.2 Parallel Trend Hypothesis

In an "ideal world" where the difference-in-difference methodology would purely apply, we should use as a control group the exact same set of treated banks, the *only* difference being that banks in the control group would not have been designated as G-SIBs. Such configuration is obviously impossible in the real world. Indeed, non–G-SIB are from the beginning smaller or less systemic than G-SIBs. Furthermore, some non–G-SIBs may also be subject to additional requirements, especially when they are designated as domestic systemically important banks (D-SIBs), even if this framework decided at the jurisdiction level is usually more recent and less homogeneous than the one of G-SIBs.

Thus, as a *second-best* option in this paper, we use all other large international banks not designated as G-SIBs as a kind of control group to capture the "industry trends" (i.e., the γ coefficient). The underlying assumption in this methodology is that both groups of banks (G-SIBs and non–G-SIBs) follow parallel trends before the designation, and that they would have continue to do so if the designation would not have occurred.[22] If the latter is clearly not testable, at least we can empirically check the former.

We can graphically assess on figures 2 and 3 whether the averaged characteristics of the two subgroups tended to evolve similarly before

[22]We also checked the parallel trends across different geographical regions (Europe, North America, China, and the rest of the world). We find no major differences in the evolutions of these variables for these four regions before 2011. However, the level of some indicators can differ for China. Therefore, we run an additional robustness check in section 6 (table 8) excluding Chinese banks from the sample. Results remain broadly unchanged.

the first designation of G-SIBs in November 2011. In order to assess more formally this "parallel trend hypothesis" (PTH) we perform a test, in line with what Danisewicz, Reinhardt, and Sowerbutts (2017) proposed. For each year preceding the first designation of G-SIBs we compute the annual growth rate of the dependent variables and then compare these growth rates between the two subgroups. Applying mean-difference t-tests, we determine whether these variables show significantly different annual evolutions between G-SIBs and non–G-SIBs. That is to say, if we notice a difference in the growth rates of G-SIBs versus non–G-SIBs, even at 10 percent significance level, then the parallel trend hypothesis will be deemed not fully met for this particular year. Table 4 summarizes the results of these tests of the parallel trend hypothesis for all our dependent variables listed in table 1.

Looking at the overall result of table 4, we see that the PTH seems met for most of the variables over the years between 2006 and 2011. The few violations of the PTH mostly tend to appear in years 2007, 2008, and 2009, which might be related to a different impact of the crisis on the two subgroups. When such violation of the PTH appears for a given year for a dependent variable, then we will include the time-dummy variable PTH_t in the regression. It will take value 1 for all i if the parallel trend hypothesis seems violated at time t for the dependent variable $Y_{i,k,t}$, even at a 10 percent significance level, and value 0 otherwise. Hence, it will try to capture the underlying source of divergence between the two subgroups that occurred during that particular year. When the PTH_t variable is introduced, it will be indicated at the bottom of each regression table in section 5.

4.3 Propensity Score Matching

In order to reduce heterogeneity between the G-SIB and non–G-SIB subgroups, an alternative approach can be used to construct the control group. We tested a propensity score matching (PSM) methodology and followed Stuart (2010). First, using a logit model, we computed the propensity scores of all banks (i.e., the probability of being designated as a G-SIB, given some covariates), using balance sheet, income statement, and profitability characteristics as

Table 4. Test of the Parallel Trend Hypothesis

Variable	2006			2007			2008		
	ΔGR	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**
TA gr	2.80	0.43		16.0	0.22		−1.3	0.27	
TA/GDP	0.02	0.37		0.00	0.98		0.09	0.09	*
T1 gr				−13.0	0.19		−3.6	0.63	
T1/TA	0.01	0.75		−0.1	0.01	**	−0.0	0.54	
T1/RWA	0.02	0.58		−0.1	0.00	***	0.13	0.00	***
CASH CB/TA	−0.0	0.79		0.44	0.20		−0.2	0.34	
LOANS CUST/TA	0.02	0.23		−0.0	0.81		−0.0	0.15	
SUB DEBT/TL	−0.0	0.35		−0.0	0.40		−0.2	0.28	
	2009			**2010**			**2011**		
Variable	**ΔGR**	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**
TA gr	−1.1	0.61		1.31	0.45		0.68	0.03	
TA/GDP	−0.0	0.94		0.01	0.37		0.00	0.91	
T1 gr	2.57	0.02	**	1.36	0.61		−0.3	0.33	
T1/TA	0.06	0.26		0.03	0.31		−0.0	0.06	*
T1/RWA	−0.0	0.41		0.03	0.17		−0.0	0.50	
CASH CB/TA	0.64	0.07	*	0.07	0.57		−0.9	0.06	*
LOANS CUST/TA	0.10	0.00	***	−0.0	0.22		−0.0	0.18	
SUB DEBT/TL	0.21	0.00	***	0.02	0.72		0.00	0.95	

(*continued*)

Table 4. (Continued)

Variable	2006			2007			2008		
	ΔGR	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**
NET PROF/OP INC	−0.1	0.22		0.03	0.85		3.80	0.21	
ROA	2.88	0.32		0.22	0.47		0.30	0.56	
ROE	3.78	0.29		−0.0	0.66		0.14	0.79	
RWA Density	−0.0	0.74		0.01	0.57		−0.2	0.14	
NPL/LOANS	0.08	0.31		0.04	0.84		0.12	0.58	
LOAN YIELD	0.08	0.03	**	−0.0	0.36		−0.1	0.07	*
DEP COST	0.15	0.19		−0.0	0.88		−0.2	0.00	***
NIM	0.04	0.52		0.04	0.59		0.16	0.17	
Variable	**2009**			**2010**			**2011**		
	ΔGR	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**	**ΔGR**	**p-val.**	**Sig.**
NET PROF/OP INC	−2.9	0.28		−3.6	0.23		1.10	0.11	
ROA	−2.0	0.37		−1.1	0.00	***	0.22	0.71	
ROE	−1.8	0.35		−1.0	0.00	***	0.24	0.65	
RWA Density	0.07	0.00	***	−0.0	0.46		−0.0	0.09	*
NPL/LOANS	−0.0	0.78		0.64	0.27		0.03	0.43	
LOAN YIELD	−0.0	0.81		−0.0	0.09	*	−0.0	0.36	
DEP COST	−0.2	0.00	***	−0.0	0.18		−0.1	0.21	
NIM	0.07	0.24		−0.0	0.27		−0.0	0.07	*

Notes: ΔGR indicates the difference between the year-on-year growth rates of the two subgroups of banks (G-SIBs and non–G-SIBs). We also report the p-value of the mean-difference t-test between these two growth rates. When we notice a significant difference, even at the 10 percent significance level, then the parallel trend hypothesis will be deemed not fully met for this particular year. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

explanatory variables. Then, each G-SIB was matched to the non–G-SIB with the closest propensity score (without replacement). All remaining non–G-SIBs were simply ignored. Finally, we rerun our regressions using this alternative control group. Results are displayed in table 8, column "PS Matching." Since they are very similar to our main approach described in the two previous subsections, both in terms of significance and magnitude, we decided to retain as the main methodology our initial strategy and consider the PSM as a robustness check analysis since it is based on a smaller sample.

5. Assessing Changes in Banks' Business Model

This section presents the regression results regarding the different aspects of the banks' business models. We first focus on some key balance sheet and prudential ratios (including balance sheet growth and structure, as well as capital adequacy). Then we turn to an analysis of profitability, risk-taking behavior, and yields.

5.1 Balance Sheet and Prudential Ratios

5.1.1 Growth of the Balance Sheet

Looking at the regression results in table 5, we notice a very significant negative sign for the interaction variable (δ coefficient) for the growth rate of total assets. It decreases by 5.8 percentage points (pp) on average for G-SIBs starting with 2012, everything else equal.

Result 1. *Everything else equal, G-SIBs have strongly curbed the expansion of their balance sheet since their first designation by the FSB.*

Note that, as shown in table 2, growth rates of total assets remain—at least slightly—positive on average for the two types of banks over the two subperiods. However, this relative slowdown of the expansion of G-SIBs' balance sheet, which we can attribute to the designation, is strongly consistent with the steady decline over time of the share of assets held by G-SIBs versus non–G-SIBs illustrated in the right panel of figure 1. When total asset is scaled by GDP, we also find strong evidence of the relative decrease of the weight of G-SIBs into their national economies.

Table 5. Balance Sheet and Prudential Ratios: Regression Results

	Dependent Variable							
	TA gr	**TA/GDP**	**T1 gr**	**T1/TA**	**T1/RWA**	**CASH CB/TA**	**LOANS CUST/TA**	**SUB DEBT/TA**
(β) GSIB	0.177	37.981**	0.100	−0.907**	−0.748	−0.300	−4.475	0.294
	(1.605)	(16.107)	(1.780)	(0.375)	(0.922)	(0.844)	(4.137)	(0.347)
(γ) Post2011	−1.651**	2.301	−3.730**	0.509***	1.974***	2.312***	3.555***	−0.234
	(0.834)	(1.499)	(1.737)	(0.107)	(0.451)	(0.804)	(1.160)	(0.157)
(δ) GSIB	**−5.763*****	**−14.704****	**−2.512**	**0.589*****	**−0.133**	**2.340*****	**−1.120**	**0.301***
× Post2011	(1.392)	(7.234)	(2.039)	(0.200)	(0.569)	(0.809)	(1.545)	(0.169)
Size	0.019		−0.418	0.337**	−0.675*	0.232	−5.499***	−0.221*
	(0.636)		(0.765)	(0.167)	(0.350)	(0.387)	(1.070)	(0.115)
LOANS/TA			−0.074**	0.004	−0.058**			
			(0.029)	(0.008)	(0.025)			
DEP/TL			0.006	0.013*	0.013			
			(0.034)	(0.007)	(0.018)			
ROA			4.794***	0.459***	0.282			
			(1.579)	(0.117)	(0.224)			
Intercept	5.428	6.287	34.671**	−2.008	26.618***	2.900	151.677***	6.951***
	(12.297)	(5.752)	(16.821)	(3.407)	(6.627)	(7.983)	(21.167)	(2.148)
Obs.	1,023	1,083	883	946	930	681	681	679
Adj.-R^2	0.333	0.023	0.266	0.227	0.383	0.547	0.103	0.122
Macro Control Var.	YES	YES	YES	YES	YES	YES	YES	YES
PTH Dummy = 1 for Nonparallel Trends in Year(s)		2008	2009	2007 2011	2007 2008	2009 2011	2009	2009
Bank-Specific Control Variables included for Some Variables of This Set								
Size: Balance Sheet Size (Log of Total Assets) LOANS/TA: Loans to Total Assets DEP/TL: Deposits to Total Liabilities ROA: Return on Assets								

Notes: Figures are in percentage points. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

This result 1 is then fairly consistent with the design of the BCBS's methodology used to identify G-SIBs, as it tends to indicate that G-SIBs try to reduce their systemic footprints by actively reducing the expansion of their balance sheet, as the size indicator is of paramount importance in the identification of G-SIBs performed by the BCBS (cf. appendix B for more details). It is then not surprising that this indicator seems strategically managed in order to avoid, or at least minimize, the additional regulatory constraints that follow the designation of a bank as a G-SIB. Note that conversely some banks might also be tempted to increase their systemic footprint so as to be designated as G-SIB and benefit from an increased implicit bailout guarantee. However, such behavior would tend to bias our δ estimate toward zero, hence it does not contradict result 1.

We also tested whether such downward pressure was noticed for other indicators used in the BCBS's methodology. Out of the 12 indicators used by the BCBS in its G-SIB identification methodology, we could replicate 6 of them with enough accuracy using the S&P Global Market Intelligence database. Apart from the growth rate of total assets, although we find a negative coefficient for most of them, the strategic reduction of the systemic footprint does not appear significant for the other systemic indicators of the BCBS methodology, as they can be proxied from public data.[23]

5.1.2 Prudential Ratios

Our focus is now drawn toward solvency patterns.[24] Both structural and time differences can be noticed. We find a significant structural gap in terms of leverage ratio (T1/TA) between G-SIBs and non–G-SIBs (coefficient β). This implies that G-SIBs are generally more leveraged than non–G-SIBs, with a leverage ratio 0.91 percentage point lower than the one of non–G-SIBs, everything else equal. Such

[23]This complete analysis of the proxy indicators used in the BCBS's methodology can be obtained from the authors upon request.

[24]For the growth rate of tier 1 capital, and for the two capital adequacy ratios (leverage ratio and tier 1 solvency ratio), we include as bank-specific control variables two ratios describing the level of retail activities in banks' balance sheets: the share of loans within total assets and the share of deposits within total liabilities. We also include the return on average asset to take into account differences in assets profitability, which is likely to impact banks' ability to raise capital.

structural gap between G-SIBs and non–G-SIBs does not appear significant for the risk-weighted capital ratio (T1/RWA). For these two capital ratios, the coefficient γ is positive and strongly significant, so all banks display higher solvency levels in the second period. This is consistent with the adoption of the Basel III regulatory framework that imposed all banks to boost their solvency ratios.

The main interest variable, $GSIB \times Post2011$, brings additional interesting evidence, although counterintuitive at a first view: the coefficient δ is significant only for the leverage ratio and not for the risk-weighted solvency ratio. Since the designation of a bank as a G-SIB automatically results in an additional capital buffer on top of the minimum risk-weighted solvency requirements, one may have expected a positive and significant coefficient here. In fact, such mechanical explanation does not take into account the general race for higher solvency ratios. Many banks, either G-SIBs or not, have increased their solvency ratio more than requested by the Basel III standards, as a response to market and supervisory pressure (such as "pillar 2" additional requirements, for instance). Such general hoarding of new capital is reflected in our results by the coefficient δ which is not significant for the growth rate of tier 1 capital (T1 gr): G-SIBs did not increase their tier 1 more than their peers following their designation. This may also come from the fact that some banks among the non–G-SIBs might be subject to equivalent additional capital requirements, such as a D-SIB buffer.[25] These two elements could partly explain why the G-SIB designation has no significant effect on the G-SIBs' risk-weighted capital adequacy ratio in our results.

On the contrary, we notice a significant and substantial effect on the leverage ratio, which shows an additional increase by 0.59 pp for G-SIBs on top of the general improvement of 0.51 pp that affected all banks in the second period. As G-SIBs used to be more leveraged than other banks before 2011, this further improvement of the leverage ratio helped them bridge this leverage gap, at least partly. It is noticeable that such an evolution occurred years before the discussion about a possibly higher leverage ratio requirement for G-SIBs began.

[25] If they are listed as "domestic systemically important banks" by their national supervisory authority; please see BCBS (2012).

Result 2. *The G-SIBs designation seems to have triggered an additional increase of the leverage ratio for the subgroup of G-SIBs since 2012, tending to bridge the structural leverage gap noticed between G-SIBs and non–G-SIBs. Surprisingly, the designation does not seem to have an impact on the levels of the risk-weighted capital ratio in the second period.*

5.1.3 Balance Sheet Structure

Beyond the pressure to raise capital, the G-SIB reform agenda might also lead banking institutions to modify their balance sheet. In order to reach the new capital requirements, an alternative to capital increase would be to change the composition of the balance sheet or to improve the quality of asset portfolio. One can also expect that banks will be incentivised to increase the share of stable loss-absorbing liabilities. To assess the evolutions of banks' balance sheets, we use a detailed breakdown of both assets and liabilities.[26] All variables of this breakdown of banks' balance sheet have been tested to provide an in-depth assessment of potential structural changes attributable to the G-SIB designation. For the sake of simplicity and brevity, only results with the most important policy implications are reported in this paper. However, results for all other variables for both asset and liability structure are gathered into a supplementary document available upon request to the authors.

With respect to asset portfolio, two main changes have to be highlighted. First, we find a significant positive impact (+2.3 pp) of the G-SIB reform agenda on cash and central bank holdings for the subsample of G-SIBs compared with other banks. This result

[26]Over the full database that comprises a maximum of 1,164 observations (97 banks time 12 years), we get 681 observations for assets structure and 679 observations for liabilities. On average, total assets can be broken down into cash and balances with central banks (6.0 percent of assets over the full panel), loans to banks (6.9 percent), loans to nonfinancial customers (51.6 percent), trading account (7.2 percent), available for sales securities (7.6 percent), held to maturity securities (2.9 percent), derivatives (6.6 percent), other financial assets (1.2 percent), intangible assets (0.7 percent), and other assets (9.3 percent). Total liabilities can be split into deposits from banks (11.6 percent of liabilities over the full sample), customer deposits (53.1 percent), subordinated debt (1.8 percent), senior debt obligations (17.5 percent), derivatives (7.0 percent), other financial liabilities (2.1 percent), and other liabilities (6.9 percent).

brings empirical proof of the efforts made by G-SIBs to catch up with a higher share of liquid assets of good quality from a relatively lower level recorded over the period 2005–11. This effect is likely to have been partially driven by expansive monetary policies around the world (quantitative easing programs and low interest rates) and the implementation of a new liquidity framework within the post-crisis reform agenda. Indeed, cash and balances with central banks are high-quality liquid assets taken for 100 percent as a buffer in the context of the liquidity coverage ratio (LCR). Even though the LCR is not a G-SIB-specific regulation, the fact that G-SIBs tended to lag behind in terms of cash holdings put a stronger pressure on these institutions.[27] Moreover, as one can see in figure 2, G-SIBs started to increase the share of cash since the crisis; this can easily be explained through market pressure to increase the holdings of high-quality liquid assets (the so-called flight to liquidity and quality). Still, taking into account the crisis effect in the regressions, using a set of macroeconomic control variables, we find that the G-SIB designation pushed further this reallocation of assets toward larger cash holdings.

Secondly, the share of loans to nonfinancial customers in the balance sheet was not affected by the overall regulatory framework designated for G-SIBs. It appears that over the second period all banks have raised their holdings of loans on average (as indicated by the coefficient γ of +3.6 pp). The estimated coefficient δ of the interaction variable is negative although not statistically significant. Such finding is in line with Admati and Hellwig (2014) sustaining that, according to the Modigliani-Miller view, higher capital requirements should have a limited impact on the bank's lending policy. It therefore provides empirical evidence against some industry's concerns that higher regulatory requirements would lead to a drop in credit supply.

Result 3. *Everything else equal, the most important change in broad asset structure driven by the G-SIB designation has been a 2.3 pp increase in the share of cash and central bank reserves that tended to*

[27] Our findings are in line with the conclusions of Birn, Dietsch, and Durant (2017) highlighting that between 2011 and 2014, G-SIBs effectively increased liquid assets more than other banks.

affect the structural gap in the share of cash recorded before 2011 compared with non–G-SIBs. Beyond that, the rest of the balance sheet does not seem to have been affected by the G-SIB designation, especially the ability of G-SIBs to provide loans and finance the real economy remained unchanged.

Turning now to the analysis of the structure of liabilities, the estimated coefficients δ suggest that the G-SIB designation and its regulatory consequences did not drive major shifts in the liabilities composition of G-SIBs, except a slightly significant increase of the share of subordinated debt (+0.3 pp after 2011 compared with non–G-SIBs). This finding may be linked to the introduction of the TLAC requirement, as some of the underlying debt instruments can be eligible to fulfill the required loss-absorbing capacity of the bank.

Result 4. *Everything else equal, apart from a small increase of subordinated debt, the G-SIB designation does not seem to have changed the liability structure of G-SIBs' balance sheet.*

5.2 Profitability, Risk-Taking, and Yield Ratios

We now focus on other aspects of banks' business model and analyze measures of profitability, risk-taking behavior, and yields. The challenges posed by new regulations and the macroeconomic environment are likely to affect the results of financial institutions. Banks designated as G-SIBs since 2011 are subject to more stringent regulatory requirements, which is generally considered costly by regulated banks (Institute of International Finance 2010). At the opposite, several empirical studies highlight that an improvement of the quality of capital reduces banks' risk-taking and leaves profitability unchanged in the long run (King 2010; Kashyap, Stein, and Hanson 2010). The aim of the analysis in this subsection is to examine the extent to which the regulatory driven changes have affected the risk-taking behavior, the cost of funding, and ultimately the profitability of banks designated as G-SIBs since 2011.

5.2.1 Profitability

Our investigation on the income statement composition provided clear evidence of the existence of a major structural difference in

the revenue mix of the two groups: G-SIBs report a much lower income generated by interest-bearing activities compared with other banks (non–G-SIBs) while the revenues from trading securities are considerably higher for the former subgroup. With regard to time variations, net gains on securities have increased for all banks during the second subperiod to the detriment of net interest revenues, which is consistent with the macroeconomic conditions characterized by low interest rates and the flattening of the yield curve. On the other hand, the model fails to find evidence that the designation of G-SIBs has significantly affected whatsoever their income statement composition, and especially their net profit.

Result 5. *The FSB designation of G-SIBs seems not to have had any statistically significant impact on their net profit (scaled by operating income).*

We observe from descriptive statistics (see table 2 and figure 3) that G-SIBs and non–G-SIBs have rather comparable profitability levels in terms of net profit, ROA, and ROE at the beginning of the study period, i.e., 2005–07. Then G-SIBs tend to be more heavily affected during the 2008–09 crisis. Finally, in the aftermath of the crisis, profitability is recovering for all banks relative to the crisis level, but G-SIBs' profitability remains at a lower level compared with their peers.

The results of the regressions fail to confirm the existence of a structural difference (β coefficient) between the two subgroups of banks over the full period (2005–16), all things being equal. The second subperiod (2012–16) is characterized by a significantly higher profitability than the first one (i.e., 2005–11), which is rather consistent given the fact that the first subperiod includes the financial crisis. Such overall improvement of profitability can be seen for the three profitability indicators. As a consequence, the net profit (scaled by operating income) appears 21.6 pp larger in the second subperiod for the complete set of banks (γ coefficient).

Our empirical results in table 6 suggest that becoming a G-SIB had a significant negative impact on the ROE (–3.1 pp), which more than offset the upward profitability trend (+1.9 pp) noticed over the period for the whole sample of institutions. Econometrically, we do not find any impact of the designation on the return on assets

Table 6. Profitability, Risk-Taking, and Yield: Regression Results

	Dependent Variable							
	NET PROF/ OP INC	**ROA**	**ROE**	**RWA Density**	**NPL/ LOANS**	**LOAN YIELD**	**DEP COST**	**NIM**
(β) GSIB	24.457	−0.024	1.782	−3.784	0.737	−0.899*	−0.418**	−0.529*
	(15.034)	(0.093)	(1.566)	(3.615)	(0.692)	(0.497)	(0.193)	(0.295)
(γ) Post2011	21.553***	0.157***	1.853**	−2.714**	0.154	−0.087	−0.122	−0.064
	(8.073)	(0.042)	(0.790)	(1.256)	(0.242)	(0.110)	(0.120)	(0.082)
(δ) GSIB	**−4.610**	**−0.074**	**−3.064***	**4.609***	**−0.675***	**0.096**	**0.086**	**−0.051**
× Post2011	(7.309)	(0.053)	(1.056)	(1.432)	(0.348)	(0.134)	(0.138)	(0.087)
Size	−12.531*	0.046	−0.246	3.011***	−0.612**	−0.179	0.044	−0.072
	(7.580)	(0.037)	(0.652)	(1.152)	(0.290)	(0.114)	(0.081)	(0.067)
LOANS/TA	0.291	0.001	0.039	0.294***	−0.009	−0.017*	0.005	0.001
	(0.215)	(0.002)	(0.032)	(0.083)	(0.014)	(0.009)	(0.004)	(0.006)
DEP/TL	−0.155	0.004***	0.065*	0.001	−0.017	−0.014**	−0.020***	0.005
	(0.289)	(0.001)	(0.036)	(0.059)	(0.013)	(0.007)	(0.004)	(0.004)
RWA Density	−0.013							
	(0.207)							
Intercept	223.261	−0.872	2.801	−4.787	13.600***	10.289***	1.491	3.277**
	(150.737)	(0.741)	(13.333)	(22.710)	(5.254)	(2.278)	(1.783)	(1.374)
Obs.	637	1,026	1,007	994	998	686	686	686
Adj.-R^2	0.100	0.404	0.364	0.364	0.204	0.676	0.729	0.317
Macro Control Var.	YES	YES	YES	YES	YES	YES	YES	YES
PGH Dummy = 1 for Nonparallel Trends in Year(s)		2010	2010	2009 2011		2006 2008 2010	2008 2009	2011
Bank-Specific Control Variables included for Some Variables of This Set								
Size: Balance Sheet Size (Log of Total Assets) LOANS/TA: Loans to Total Assets DEP/TL: Deposits to Total Liabilities RWA Density: Total RWA over Total Assets								

Notes: Figures are in percentage points. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

of G-SIBs, as the fall in their ROA is triggered by the crisis and not the designation. Therefore, taking the ROA as exogenous, and everything else equal, we interpret the negative impact of the designation on the return on equity (ROE) as a "mechanical" effect of the general improvement of G-SIBs' leverage ratio (LR), as it can easily be seen looking at the accounting equation (2) below.

$$\begin{aligned} ROE = \frac{R}{TE} &= \frac{R}{TA} \times \frac{TA}{TE} \\ &= ROA \times \frac{1}{LR} \qquad \Rightarrow \qquad ROA \times \frac{1}{\nearrow LR} = \searrow ROE \end{aligned} \tag{2}$$

Result 6. *There is no empirical evidence of any G-SIB specificity in the level and change in the profitability of assets (ROA). On the contrary, G-SIBs' return on equity (ROE) appears negatively affected through a deleveraging effect induced by the G-SIB regulation.*

5.2.2 Risk-Taking Behavior

One can notice a sizable relative increase of the RWA density for G-SIBs in the second subperiod (+4.6 pp) while non–G-SIBs record a slight reduction of their RWA density. This situation could be interpreted as a willingness from banks to pursue riskier activities, and the moral hazard behavior springs to mind, but it may not be the main reason. Birn, Dietsch, and Durant (2017) tend to underline that off-balance-sheet (OBS) activity increased only for G-SIBs starting in 2011.[28] Such increase of OBS items would then translate into an increase of RWAs but not of total assets (by construction), which would ultimately result in an increase of the RWA density of G-SIBs. Meanwhile, such off-balance-sheet activities (for example, guarantees and undrawn credit lines) are not riskier than balance sheet activities, if correctly measured.

Secondly, the increase in the amount of RWAs for G-SIBs could be partly explained by the implementation of Basel III standards for all banks through the period, combined with G-SIBs' higher

[28]This is an *indirect* observation based on the difference between the total leverage exposure measure, which comprises OBS items, and total assets, which does not.

exposure to market activities and particularly to counterparty credit risk and market risk. Indeed, the revision of market risk framework (under Basel 2.5 and Basel III) drove important increases in risk-weighted assets measures (counterparty risk capital charges, higher asset value correlation parameter for exposures to certain financial institutions, higher risk weights for securitized assets or derivatives).[29] Hence, this change of weights would have affected differently the two groups of banks and would have also triggered an increase of the average risk weight of G-SIBs' balance sheet, irrespective of any change in activity.

Finally, we cannot fully exclude the remaining explanation that some G-SIBs might have started to gradually shift their assets toward more heavily weighted (i.e., riskier) assets. However, if such voluntary risk-shifting is occurring for some banks in search for higher returns, it has not yet materialized in the intended improved profitability of G-SIBs' assets, neither in an increase of nonperforming loans (NPL). On the contrary, the share of NPL even seems to have been slightly reduced for G-SIBs following the designation.

Whatever the explanation for the underlying phenomenon of the increased RWA density of G-SIBs, this fact also brings insights for why we do not notice any significant impact of the designation on G-SIBs' risk-based solvency ratio (see section 5.1). In addition to the global race toward solvency ratios higher than minimum requirements for all banks, the higher increase of RWA density for G-SIBs also played a role, as it caught up their effort to increase tier 1, as shown in equation (3) below.

$$\frac{T1}{RWA} = \frac{T1}{TA} \times \frac{TA}{RWA}$$

$$= LR \times \frac{1}{RWA\,dens} \Rightarrow \overset{\nearrow}{LR} \times \frac{1}{\overset{\nearrow}{RWA}\,dens} = \left(\frac{\overset{\rightarrow}{T1}}{RWA}\right) \quad (3)$$

[29]See BCBS (2013b), which shows that group 1 banks' RWA increased in the aggregate by approximately 16.1 percent after applying the Basel 2.5 and Basel III frameworks.

Result 7. *The G-SIB regulation seems to have triggered an increase of their RWA density, but this does not seem to reflect a shift in the risk-taking behavior of these banks.*

5.2.3 Yields

The question that can be raised further in the analysis concerns the extent to which banks subject to higher regulatory requirements responded to the reduction in ROE. Using equation (1), we analyze the effects of G-SIB reform agenda on the cost of funding (especially for deposits), the yield of loans, and interest margins.

Over the available sample for the complete 2005–16 period (686 observations), the average yield on loans equals 5.2 percent while the average cost of deposits is 2.0 percent and the global net interest margin is 2.2 percent. The results of regressions, and particularly the estimated coefficient β, suggest that G-SIBs, compared with their peers, benefit from a structural lower cost of deposits in the range of 0.4 pp. Such funding advantage can be related to both the existence of implicit public support (cf. Schich and Toader 2017) and the greater diversification of G-SIBs (in terms of activity and geographic locations) that could lower their idiosyncratic risk in the view of investors.

Our findings suggest that, for G-SIBs, this lower cost of liabilities is transmitted to loans pricing to the extent that their average loan yield is structurally 0.9 pp lower than for non–G-SIBs. Furthermore, these structural features are stable over time for all banks, G-SIBs or not. The lack of significance for the coefficient γ of the "Post2011" time-dummy variable can be explained by the introduction of macroeconomic control variables, and particularly the 10-year sovereign debt yield that captures the impact of the evolution of the general interest rates environment. As for the interaction variable, we do not find any direct and significant impact of the G-SIB designation on these dependent variables.

Result 8. *The G-SIB designation did not have any impact on loans yields, cost of deposits, nor net interest margin. This lack of significant impact suggests that stricter regulation had no unintended effects so far on banks' and customers' funding cost. However, since the cost of funding appears to be structurally lower for G-SIBs, the*

absence of impact of the G-SIB regulation on this variable also corroborates the fact that the designation of G-SIBs did not put an end to the implicit public support.

6. Robustness Checks

6.1 Alternative Subperiods

In section 4, we described that we chose to split our panel into the two subperiods 2005–11 and 2012–16, so we included the $Post2011_t$ time-dummy variable in the regressions. As explained above, this cutoff date between 2011 and 2012 seems the more "natural," since the first list of G-SIBs was published in November 2011. However, on the one hand, someone could argue that a longer time is needed for real effects of this designation to materialize in the balance sheet/income statement of G-SIBs. This would lead to postponement of the cutoff date, for instance considering that the second subperiod only started in 2013 or 2014, instead of 2012. On the other hand, one could say that most effects may have been anticipated, either by banks themselves, or by the market.[30] This would argue for setting an earlier cutoff date—for instance, in 2011 or 2010. Therefore, we reran all the regressions displayed in section 5, each time using an alternative starting date of the second subperiod, ranging from 2010 to 2014, with 2012 being the baseline starting date used in all previous sections of the paper.

Table 7 shows the coefficient δ of the interaction variable for all dependent variables listed in table 1 and discussed in section 5 and for all alternative starting dates of the second subperiod between 2010 and 2014. As one can notice in this table, coefficients generally remain of the same magnitude, as well as their significance level. This indicates that the choice we made to consider 2012 as the start of the second subperiod—although still "arbitrary"—is not driving the results, and that similar conclusions would have been drawn if we had decided to set an earlier or later cutoff date.

[30] As mentioned by Moenninghoff, Ongena, and Wieandt (2015), the *Financial Times* published two lists of systemic banks in 2009 and 2010, before the first official publication of the FSB list in November 2011.

Table 7. Alternative Subperiods and Definition of G-SIB Subsample

δ Coefficient for Dependent Variable:	Second Subperiod Starting in:					G-SIB Binary Variable Used		
	2010	2011	2012	2013	2014	G-SIB Once	G-SIB 2011	G-SIB Always
TA gr	-5.079^{***}	-5.532^{***}	-5.763^{***}	-3.401^{**}	-2.154^{*}	-5.763^{***}	-6.31^{***}	-5.434^{***}
	(1.65)	(1.385)	(1.392)	(1.325)	(1.306)	(1.392)	(1.497)	(1.653)
TA/GDP	-14.374^{*}	-14.687^{*}	-14.704^{**}	-14.849^{**}	-13.837^{**}	-14.704^{**}	-17.472^{**}	-13.46
	(8.544)	(7.9)	(7.234)	(6.737)	(6.081)	(7.234)	(8.38)	(8.693)
T1/TA	0.45^{**}	0.483^{**}	0.589^{***}	0.65^{***}	0.646^{***}	0.589^{***}	0.541^{**}	0.49^{**}
	(0.215)	(0.204)	(0.2)	(0.199)	(0.191)	(0.2)	(0.213)	(0.222)
T1/RWA	-0.332	-0.203	-0.133	-0.426	-0.63	-0.133	0.103	-0.248
	(0.505)	(0.523)	(0.569)	(0.601)	(0.626)	(0.569)	(0.584)	(0.542)
T1 gr	-4.99	-4.641^{**}	-2.512	-1.514	-0.828	-2.512	-3.211	-2.024
	(3.079)	(2.332)	(2.039)	(1.721)	(1.78)	(2.039)	(2.057)	(2.023)
CASH CB/TA	2.7^{***}	2.518^{***}	2.34^{***}	2.249^{***}	2.196^{***}	2.34^{***}	2.319^{***}	2.266^{***}
	(1.028)	(0.905)	(0.809)	(0.732)	(0.702)	(0.809)	(0.803)	(0.833)
CUST LOANS/TA	-1.659	-1.592	-1.12	-0.244	-0.181	-1.12	-1.099	-0.327
	(2.031)	(1.746)	(1.545)	(1.365)	(1.295)	(1.545)	(1.538)	(1.605)
SUB DEBT/TL	0.33^{*}	0.324^{*}	0.301^{*}	0.323^{**}	0.271^{*}	0.301^{*}	0.281	0.35^{*}
	(0.177)	(0.178)	(0.169)	(0.161)	(0.158)	(0.169)	(0.178)	(0.18)
NET PROF/OP INC	6.064	1.798	-4.61	-6.663	-9.781^{*}	-4.61	0.333	-7.774
	(10.907)	(11.4)	(7.309)	(5.449)	(5.822)	(7.309)	(10.098)	(9.043)
ROA	-0.063	-0.101^{*}	-0.074	-0.031	-0.039	-0.074	-0.092^{*}	-0.08
	(0.065)	(0.061)	(0.053)	(0.054)	(0.052)	(0.053)	(0.05)	(0.05)
ROE	-2.302^{*}	-3.284^{***}	-3.064^{***}	-2.052^{**}	-1.841^{**}	-3.064^{***}	-3.084^{***}	-2.306^{**}
	(1.399)	(1.268)	(1.056)	(0.971)	(0.92)	(1.056)	(1.079)	(1.072)
NPL/LOANS	-0.393	-0.553	-0.675^{*}	-0.743^{**}	-0.699^{**}	-0.675^{*}	-0.509	-0.071
	(0.379)	(0.341)	(0.348)	(0.343)	(0.31)	(0.348)	(0.367)	(0.372)
RWA Density	4.108^{**}	3.914^{***}	4.609^{***}	5.429^{***}	5.608^{***}	4.609^{***}	3.468^{**}	3.733^{**}
	(1.619)	(1.514)	(1.432)	(1.409)	(1.408)	(1.432)	(1.598)	(1.616)
LOAN YIELD	-0.145	-0.039	0.096	0.31^{**}	0.337^{**}	0.096	0.015	0.051
	(0.156)	(0.13)	(0.134)	(0.158)	(0.165)	(0.134)	(0.154)	(0.159)
DEP COST	-0.018	0.012	0.086	0.225	0.198	0.086	-0.002	0.002
	(0.138)	(0.134)	(0.138)	(0.142)	(0.126)	(0.138)	(0.139)	(0.14)
NIM	-0.056	-0.058	-0.051	0.003	0.045	-0.051	-0.083	-0.064
	(0.111)	(0.1)	(0.087)	(0.082)	(0.082)	(0.087)	(0.095)	(0.099)

Note: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

6.2 Alternative Definition of "G-SIB" Subsample

Similarly, section 4 explains that the $GSIB_{i,k}$ dummy variable indicates all banks that have been identified as G-SIB at least once by the FSB between 2011 and 2016. In table 7, this baseline definition of the G-SIB subsample is referred to as "G-SIB Once." Alternative definition of this "G-SIB" subsample could have been used instead. Therefore, we reran all regressions presented in section 5 using two alternative G-SIB binary variables. With the first alternative we simply focus on the initial list of G-SIBs published by the FSB in November 2011 and simply ignore the few changes of this list that intervened in the following years. We refer to this first alternative dummy variable as "G-SIB 2011" in the regression table 7. The second alternative consists in restraining the binary variable to banks that have constantly been listed as G-SIBs between 2011 and 2016, and therefore use a stable list of permanent G-SIBs. We refer to this second alternative dummy variable as "G-SIB Always" in table 7.[31] We notice that most results remain the same whatever definition for the G-SIB subsample is used.

6.3 Taking into Account the Financial Crisis

The baseline equation (1) used in the paper includes a set of macroeconomic control variables, notably the unemployment rate and the GDP growth that should—at least partially—capture the effect of a macroeconomic downturn. However, in order to specifically isolate the impact of the 2008–09 financial crisis, on top of the macroeconomic control variables, we can add a "crisis" time-specific dummy variable taking value 1 only for years 2008 and 2009, like in equation (4) below. The results of this specification are available in column "Crisis Dummy" of table 8 and do not show major differences compared with the baseline results.

[31]The "G-SIB Always" variable identifies 26 banks. "G-SIB 2011" adds the following three banks compared with "G-SIB Always": Lloyds Banking Group, Commerzbank, and Dexia. "G-SIB Once" adds the following five banks compared with "G-SIB 2011": Industrial and Commercial Bank of China, China Construction Bank Corporation, Agricultural Bank of China Limited, BBVA, and Standard Chartered.

Table 8. Alternative Econometric Specifications

δ Coefficient for Dependent Variable:	Specification											
	Baseline	**Crisis Dummy**	**Buffer Rates**	**First Bucket**	**Country FE**	**Country FE * 2**	**Regional FE**	**Without China**	**Gov. CDS Spread**	**Europe**	**No State Support (EU)**	**PS Matching**
	Eq. (1)	**Eq. (4)**	**Eq. (5)**	**Eq. (1)**	**Eq. (6)**	**Eq. (7)**	**Eq. (6)**	**Eq. (1)**	**Eq. (1)**	**Eq. (1)**	**Eq. (1)**	**Eq. (1)**
TA gr	−5.763***	−5.818***	−2.783***	−5.49***	−5.963***	−4.701***	−5.818***	−6.828***	−6.664***	−5.577***	−4.999**	−5.134***
	(1.392)	(1.386)	(0.9)	(1.543)	(1.514	(1.472)	(1.386)	(1.595)	(1.64)	(1.998)	(2.327)	(1.507)
TA/GDP	−14.704**	−14.791**	−6.603	−15.115	−13.152**	−9.623**	−14.791**	−16.994**	−7.662*	−20.788*	−18.835	−13.471*
	(7.234)	(7.162)	(4.108)	(9.803)	(6.699)	(4.189)	(7.162)	(8.37)	(4.323)	(11.12)	(13.046)	(6.932)
T1/TA	0.589***	0.592***	0.415***	0.369	0.642***	0.399**	0.592***	0.491***	0.414**	0.362*	0.446*	6.408**
	(0.2)	(0.199)	(0.124)	(0.226)	(0.197)	(0.171)	(0.199)	(0.181)	(0.189)	(0.213)	(0.243)	(0.201)
T1/RWA	−0.133	−0.187	−0.247	−0.081	0.018	−0.378	−0.187	−0.263	−0.695	−1.71**	−1.947**	0.697
	(0.569)	(0.573)	(0.292)	(0.662)	(0.631)	(0.532)	(0.573)	(0.595)	(0.029)	(0.739)	(0.867)	(0.517)
T1 gr	−2.512	−2.819	−0.847	−2.386	0.275	−1.435	−2.819	−4.989***	−2.746	−0.948	−1.197	−2.036
	(2.039)	(2.108)	(1.033)	(2.337)	(1.913)	(1.991)	(2.108)	(1.852)	(2.278)	(3.118)	(3.253)	(2.211)
CASH CB/TA	2.34***	2.24***	1.218**	2.501***	2.422***	2.094***	2.24***	2.587***	2.268***	2.474**	2.444*	2.048***
	(0.809)	(0.806)	(0.494)	(0.864)	(0.763)	(0.655)	(0.806)	(0.895)	(0.864)	(1.261)	(1.484)	(0.649)
CUST LOANS/TA	−1.12	−1.091	−0.396	−1.441	−1.257	−0.903	−1.091	−2.742*	−0.584	−3.404*	−2.617	0.685
	(1.545)	(1.53)	(0.969)	(1.631)	(1.473)	(1.424)	(1.53)	(1.555)	(1.572)	(2.064)	(2.43)	(1.488)
SUB DEBT/TL	0.301*	0.298*	0.185*	0.261	0.183	0.157	0.298*	0.191	0.151	0.206	0.104	−0.009
	(0.169)	(0.169)	(0.105)	(0.178)	(0.205)	(0.169)	(0.169)	(0.192)	(0.158)	(0.213)	(0.237)	(0.208)
NET PROF/OP INC	−4.61	−2.099	−11.315*	−0.829	−0.606	−2.993	−2.099	−8.96	−8.759	−10.248	−0.443	−4.155
	(7.309)	(7.28)	(6.345)	(8.536)	(8.622)	(8.359)	(7.28)	(8.915)	(7.123)	(9.529)	(8.663)	(5.702)
ROA	−0.074	−0.052	−0.054*	−0.052	−0.093	−0.039	−0.052	−0.151***	−0.04	−0.207***	−0.165**	−0.107*
	(0.053)	(0.049)	(0.03)	(0.061)	(0.064)	(0.057)	(0.049)	(0.052)	(0.056)	(0.064)	(0.065)	(0.06)
ROE	−3.064***	−2.714***	−1.706***	−2.366**	−3.109***	−2.365**	−2.714***	−4.435***	−2.845**	−5.543***	−4.233***	−3.23***
	(1.056)	(1.001)	(0.654)	(1.157)	(1.157)	(1.076)	(1.001)	(1.153)	(1.133)	(1.466)	(1.554)	(1.17)
NPL/LOANS	−0.675*	−0.676*	−0.062	−0.835**	−0.384	−0.716*	−0.676*	−0.395	−0.671*	−1.791**	−1.092	−0.677
	(0.348)	(0.352)	(0.197)	(0.417)	(0.432)	(0.412)	(0.352)	(0.394)	(0.399)	(0.751)	(0.722)	(0.432)
RWA Density	4.609***	4.816***	3.443***	3.457**	3.809**	3.246**	4.816***	4.494***	4.156***	8.382***	8.877***	2.937**
	(1.432)	(1.415)	(0.876)	(1.549)	(1.512)	(1.302)	(1.415)	(1.469)	(1.515)	(2.147)	(2.521)	(1.332)
LOAN YIELD	0.096	0.057	−0.017	0.136	−0.1	−0.051	0.057	0.17	0.154	0.381	0.499	0.079
	(0.134)	(0.129)	(0.091)	(0.146)	(0.18)	(0.145)	(0.129)	(0.146)	(0.133)	(0.27)	(0.308)	(0.151)
DEP COST	0.086	0.086	−0.015	0.129	−0.134	0.074	0.086	0.134	0.069	−0.026	−0.019	0.26
	(0.138)	(0.138)	(0.103)	(0.141)	(0.167)	(0.123)	(0.138)	(0.148)	(0.129)	(0.3)	(0.366)	(0.171)
NIM	−0.051	−0.067	−0.02	−0.072	−0.052	−0.095	−0.067	−0.08	−0.02	0.158	0.413***	−0.88
	(0.087)	(0.088)	(0.058)	(0.095)	(0.089)	(0.086)	(0.088)	(0.089)	(0.093)	(0.115)	(0.154)	(0.103)

Notes: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t) + \varphi B_{i,k,t} + \chi C_{k,t} + \lambda Crisis_t + PTH_t + u_{i,k,t} \quad (4)$$

6.4 Including G-SIB Buffers

In this paper we use a binary variable to distinguish G-SIBs from non–G-SIBs. Such approach is justified in order to apply the difference-in-difference methodology and to get directly interpretable magnitude of the coefficients. However such a choice neglects the fact that there are several G-SIB "buckets" (groups). Therefore, as a robustness check, we replace the dummy variable $GSIB_{i,k}$ in the interaction term with the level of G-SIB buffer applied to each bank. This gives us an alternative econometric specification to equation (1).

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(Buffer_{i,k,t} \times Post2011_t) + \varphi B_{i,k,t} + \chi C_{k,t} + PTH_t + u_{i,k,t} \quad (5)$$

This alternative specification hence takes into account the various levels of the G-SIB buffers (from 1 percent to 2.5 percent). Overall results are displayed in the "Buffer Rates" column of table 8. If the sign and significance level of coefficients can still be interpreted as in equation (1), on the other hand the magnitude of coefficients are no longer comparable to the one estimated using equation (1). As one can notice, the main findings of the paper are still valid using this specification.

Furthermore, one could expect that being identified as a G-SIB in the first bucket (i.e., with the smallest systemic footprint) may not have the same consequences as being listed in the higher G-SIB buckets. Then, as a robustness check, we exclude the largest G-SIBs in order to focus only on G-SIBs in the first bucket (i.e., with systemic scores between 130 and 230 bp in the 2016 FSB's designation). Results are presented in the "First Bucket" column of table 8. Once again, the main findings of the paper are confirmed, though the effect on the leverage ratio disappears, as it seems mostly driven by the largest G-SIBs.

6.5 Geographic Dimensions

The baseline regression (1) of the paper includes a set of eight country-specific macroeconomic control variables that evolve over time. More simply, we could have used some country fixed effects (FE), as in equation (6) below, to capture time-invariant country-specific characteristics. Results of this alternative specification are shown in the "Country FE" column of table 8.

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t) + \varphi B_{i,k,t} + \chi FE_k + PTH_t + u_{i,k,t} \quad (6)$$

On top of that, we can take into account that the 2008–09 financial crisis may have affected differently all countries represented in the panel, these country fixed effects may be differentiated between the pre- and post-crisis periods as in equation (7) below. These alternative results are displayed in the "Country FE * 2" column of table 8.

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t) + \varphi B_{i,k,t} + \chi_1 FE_{k,(2005-2007)} + \chi_2 FE_{k,(2008-2016)} + PTH_t + u_{i,k,t} \quad (7)$$

Using equation (6), we can also use fixed effects by region, instead of by country, in order to take into account potential differences among regulatory frameworks in the United States, Europe, Asia, and the rest of the world. These results are shown in the "Regional FE" column of table 8.

Finally, we also rerun equation (1) excluding banks from China, as it is the largest country in the data set in terms of total assets as of end-2016. Results are presented in the "Without China" column of table 8. Once again, looking at these alternative specifications, we can broadly draw the same conclusions as those exposed in section 5.

6.6 The Influence of the State

The final alternative robustness check analysis will complement the set of macroeconomic country-specific control variables with market

data (retrieved from the Bloomberg database): we include the year-end spread level of the 10-year maturity sovereign CDS. Such additional variable will better capture the situation of countries that had to face a sovereign debt crisis, which could have had some repercussions on its national banking system. The results of this robustness check are shown in the "Gov. CDS Spread" column of table 8.

States can also influence banks through public support interventions, especially following the financial crisis. An alternative explanation for the reduction in asset growth observed in the paper could be that some banks received public financial assistance during the crisis and were subsequently forced to reduce their activity. In order to rule out this alternative hypothesis, we rerun our regressions, focusing only on European banks, excluding banks that received public assistance, as listed by the European Commission.[32] These two alternative specifications are shown in the "Europe" and "No State Support (EU)" columns of table 8, and, as one can notice, the δ coefficient for the growth rate of assets remains highly significant and of the same order of magnitude as in the baseline. Hence we can claim that this effect is not particularly driven by state supports.

7. Concluding Remarks

This empirical analysis of 97 banks over 12 years is designed to identify the changes in G-SIBs' business model characteristics after their first designation by the FSB in 2011, controlling for the changes also experienced by other banks (industry trends). First, it allows to identify initial structural differences between G-SIBs and other banks. In that respect, we show that G-SIBs are structurally more leveraged. We also find empirical evidence that G-SIBs benefit from a lower cost of deposits that is likely to indicate lower perceived idiosyncratic risk due to higher diversification and implicit public support.

Secondly, we also identify some changes that affected G-SIBs after their first designation by the FSB in 2011. Using our econometric identification methodology based on a difference-in-difference approach, we identify some key effects of the designation on G-SIBs'

[32]European Commission (2018).

activity. Using these quantitative results, this paper provides a first assessment of the effectiveness of the G-SIBs reforms undertaken after the 2008 crisis and determines whether the highlighted changes are in line with the objectives of the international regulators.

In terms of policy implications, this paper shows that some intended objectives have been achieved: the expansion of the balance sheet of G-SIBs has been drastically slowed down by the regulation. The financial leverage of the G-SIBs, structurally greater than that of the other banks before the designation, has also been reduced. Such increase of G-SIBs' capital base has strengthened their resilience, which has improved further global financial stability and social welfare. However, this "deleveraging" of the G-SIBs led to another logical consequence, although not specifically sought by the regulation: the reduction of their return on equity, due to a mechanical accounting effect.

Moreover, we show in this paper that potential negative unintended consequences of these regulations, which were pointed out either by theoretical considerations or by the fears expressed by the industry, actually did not materialize. Indeed, for the time being, we have not measured any reduction in the supply of loans to the economy, or excessive risk-taking by banks in search for higher yields, that could be attributed to these regulations.

On the other hand, as the structural funding advantage derived by G-SIBs from the implicit public guarantees appears to persist in the data, it seems that the objective of ending the status of "too big to fail" is yet to be achieved.

Appendix A. Banks included in the Panel

Table A.1. List of Banks Included in the Panel

N	Institution Name	Country	Total Assets (€bn)	Identified as G-SIB by the FSB						
				At Least Once	In 2011	In 2012	In 2013	In 2014	In 2015	In 2016
1	Dexia SA	BE	213	1	1	0	0	0	0	0
2	UBS Group AG	CH	872	1	1	1	1	1	1	1
3	Credit Suisse Group AG	CH	765	1	1	1	1	1	1	1
4	Industrial and Comm. Bank of China	CN	3,293	1	0	0	1	1	1	1
5	China Construction Bank Corp.	CN	2,860	1	0	0	0	0	1	1
6	Agricutural Bank of China Limited	CN	2,670	1	0	0	0	1	1	1
7	Bank of China Limited	CN	2,476	1	1	1	1	1	1	1
8	Deutsche Bank AG	DE	1,591	1	1	1	1	1	1	1
9	Commerzbank AG	DE	480	1	1	0	0	0	0	0
10	Banco Santander, SA	ES	1,339	1	1	1	1	1	1	1
11	Banco Bilbao Vizcaya Argentaria, SA	ES	732	1	0	1	1	1	0	0
12	BNP Paribus SA	FR	2,077	1	1	1	1	1	1	1
13	Credit Agricole Group	FR	1,723	1	1	1	1	1	1	1
14	Societe Generale SA	FR	1,382	1	1	1	1	1	1	1
15	Groupe BPCE	FR	1,235	1	1	1	1	1	1	1
16	HSBC Holdings Plc	GB	2,252	1	1	1	1	1	1	1
17	Barclays Plc	GB	1,421	1	1	1	1	1	1	1
18	Lloyds Banking Group Plc	GB	958	1	1	0	0	0	0	0
19	Royal Bank of Scotland Group Plc	GB	935	1	1	1	1	1	1	1
20	Standard Chartered Plc	GB	613	1	0	1	1	1	1	1
21	Morgan Stanley and Co. International	GB	401	1	1	1	1	1	1	1
22	UniCredit SpA	IT	860	1	1	1	1	1	1	1
23	Mitsubishi UFJ Financial Group, Inc.	JP	2,330	1	1	1	1	1	1	1
24	Mizuho Financial Group, Inc.	JP	1,511	1	1	1	1	1	1	1
25	Sumitomo Mitsui Financial Group	JP	1,457	1	1	1	1	1	1	1
26	ING Groep N.V.	NL	845	1	1	1	1	1	1	1
27	Nordea Bank AB (publ)	SE	616	1	1	1	1	1	1	1
28	JPMorgan Chase and Co.	US	2,362	1	1	1	1	1	1	1
29	Bank of America Corporation	US	2,074	1	1	1	1	1	1	1
30	Wells Fargo and Company	US	1,830	1	1	1	1	1	1	1
31	Citigroup Inc.	US	1,699	1	1	1	1	1	1	1
32	Goldman Sachs Group, Inc.	US	816	1	1	1	1	1	1	1
33	Bank of New York Mellon Corporation	US	316	1	1	1	1	1	1	1
34	State Street Corporation	US	230	1	1	1	1	1	1	1
Total for G-SIBs			47,236	34	29	28	29	30	30	30

(*continued*)

Table A.1. (Continued)

N	Institution Name	Country	Total Assets (€bn)	Identified as G-SIB by the FSB						
				At Least Once	In 2011	In 2012	In 2013	In 2014	In 2015	In 2016
35	Commonwealth Bank of Australia	AU	626	0	0	0	0	0	0	0
36	Australia and NZ Banking Group	AU	623	0	0	0	0	0	0	0
37	Westpac Banking Corporation	AU	571	0	0	0	0	0	0	0
38	National Australia Bank Limited	AU	529	0	0	0	0	0	0	0
39	KBC Group NV	BE	275	0	0	0	0	0	0	0
40	Banco do Brasil S.A.	BR	404	0	0	0	0	0	0	0
41	Itau Unibanco Holding S.A.	BR	394	0	0	0	0	0	0	0
42	Caixa Economica Federal	BR	369	0	0	0	0	0	0	0
43	Banco Bradesco S.A.	BR	347	0	0	0	0	0	0	0
44	Royal Bank of Canada	CA	805	0	0	0	0	0	0	0
45	Toronto-Dominion Bank	CA	803	0	0	0	0	0	0	0
46	Bank of Nova Scotia	CA	611	0	0	0	0	0	0	0
47	Bank of Montreal	CA	469	0	0	0	0	0	0	0
48	Canadian Imperial Bank of Commerce	CA	342	0	0	0	0	0	0	0
49	Bank of Communications Co., Ltd.	CN	1,147	0	0	0	0	0	0	0
50	Industrial Bank Co., Ltd.	CN	830	0	0	0	0	0	0	0
51	China Merchants Bank Co., Ltd.	CN	811	0	0	0	0	0	0	0
52	China Minsheng Banking Corp., Ltd.	CN	804	0	0	0	0	0	0	0
53	Shanghai Pudong Development Bank	CN	799	0	0	0	0	0	0	0
54	China Everbright Bank Company	CN	549	0	0	0	0	0	0	0
55	Ping An Bank Co., Ltd.	CN	403	0	0	0	0	0	0	0
56	Hua Xia Bank Co., Limited	CN	321	0	0	0	0	0	0	0
57	Bank of Beijing Co., Ltd.	CN	289	0	0	0	0	0	0	0
58	China Guangfa Bank Co., Ltd.	CN	279	0	0	0	0	0	0	0
59	Bank of Shanghai Co., Ltd.	CN	240	0	0	0	0	0	0	0
60	DZ BANK AG	DE	509	0	0	0	0	0	0	0
61	Landesbank Baden-Wurttemberg	DE	244	0	0	0	0	0	0	0
62	Bayerische Landesbank	DE	212	0	0	0	0	0	0	0
63	Danske Bank A/S	DK	469	0	0	0	0	0	0	0
64	Banco de Sabadell, SA	ES	213	0	0	0	0	0	0	0
65	La Banque Postale, SA	FR	230	0	0	0	0	0	0	0
66	Nomura International Plc	GB	336	0	0	0	0	0	0	0
67	Nationwide Building Society	GB	262	0	0	0	0	0	0	0
68	State Bank of India	IN	408	0	0	0	0	0	0	0
69	Intesa Sanpaolo SpA	IT	725	0	0	0	0	0	0	0
70	Cassa depositi e prestiti SpA	IT	410	0	0	0	0	0	0	0

(*continued*)

Table A.1. (Continued)

N	Institution Name	Country	Total Assets (€bn)	Identified as G-SIB by the FSB						
				At Least Once	In 2011	In 2012	In 2013	In 2014	In 2015	In 2016
71	Japan Post Bank Co., Ltd.	JP	1,617	0	0	0	0	0	0	0
72	Norinchukin Bank	JP	790	0	0	0	0	0	0	0
73	Sumitomo Mitsui Trust Holdings, Inc.	JP	455	0	0	0	0	0	0	0
74	Resona Holdings, Inc.	JP	384	0	0	0	0	0	0	0
75	Shinkin Central Bank	JP	274	0	0	0	0	0	0	0
76	Japan Housing Finance Agency	JP	214	0	0	0	0	0	0	0
77	Shinhan Financial Group Co., Ltd.	KR	312	0	0	0	0	0	0	0
78	KB Financial Group Inc.	KR	296	0	0	0	0	0	0	0
79	NongHyup Financial Group Inc.	KR	289	0	0	0	0	0	0	0
80	Hana Financial Group Inc.	KR	274	0	0	0	0	0	0	0
81	Woori Bank	KR	245	0	0	0	0	0	0	0
82	Korea Development Bank	KR	215	0	0	0	0	0	0	0
83	Cooperatieve Rabobank U.A.	NL	663	0	0	0	0	0	0	0
84	ABN AMRO Group NV	NL	394	0	0	0	0	0	0	0
85	DNB ASA	NO	292	0	0	0	0	0	0	0
86	PAO Sberbank of Russia	RU	394	0	0	0	0	0	0	0
87	Svenska Handelsbanken AB (publ.)	SE	274	0	0	0	0	0	0	0
88	Skandinaviska Enskilda Banken	SE	274	0	0	0	0	0	0	0
89	Swedbank AB (publ.)	SE	225	0	0	0	0	0	0	0
90	DBS Group Holdings Limited	SG	316	0	0	0	0	0	0	0
91	Oversea-Chinese Banking Corp.	SG	269	0	0	0	0	0	0	0
92	United Overseas Bank Limited	SG	223	0	0	0	0	0	0	0
93	Cathay Financial Holding Co., Ltd.	TW	239	0	0	0	0	0	0	0
94	Federal Home Loan Banks	US	1,002	0	0	0	0	0	0	0
95	U.S. Bancorp	US	423	0	0	0	0	0	0	0
96	PNC Financial Services Group, Inc.	US	347	0	0	0	0	0	0	0
97	Capital One Financial Corporation	US	339	0	0	0	0	0	0	0
Total for Non–G-SIBs			28,696	0	0	0	0	0	0	0

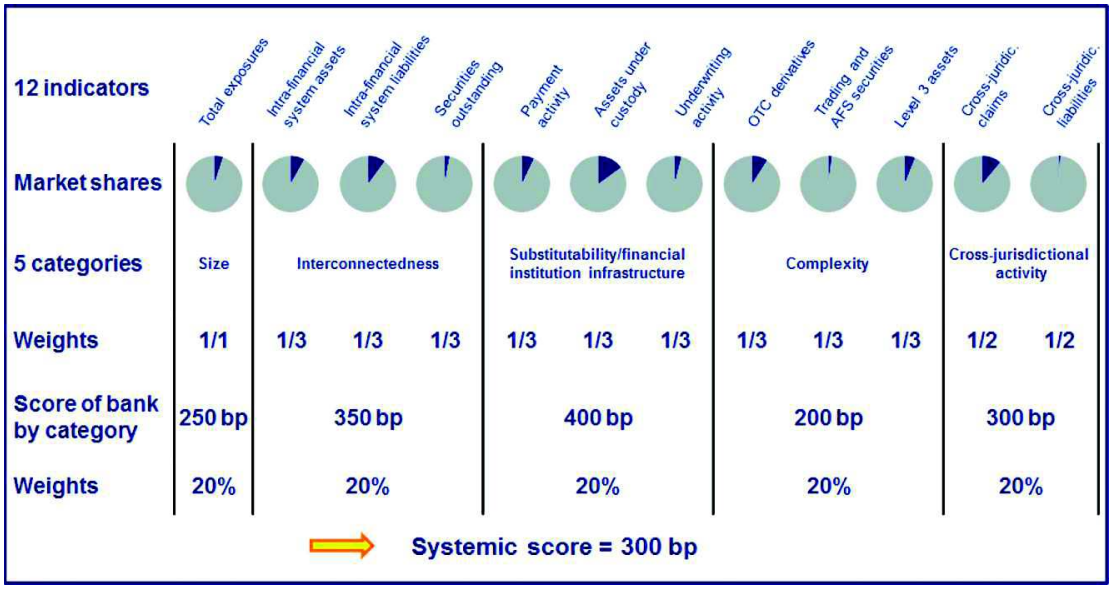
Note: Banks are ranked by (i) G-SIBs versus non–G-SIBs, (ii) country, and (iii) decreasing total assets as of end-2016.

Appendix B. Description of the Methodology Used by the BCBS to Identify G-SIBs

According to the BCBS methodology, banks' systemic footprint is assessed using a set of 12 indicators grouped into five categories. For each indicator, a "market share" is computed at bank level (i.e., the value of the indicator for bank i is divided by the sum of this indicator's values for all banks in the sample used by the BCBS). Within each of the five categories, the "market shares" of the underlying indicators are then equally weighted to compute a score in basis points. Finally, these five categories' subscores are averaged (20 percent each) to get the final systemic score. Figure B.1 provides an illustration of this methodology.

Once the systemic score is computed, banks are ordered and allocated into buckets according to their systemic score value. Only banks with systemic scores above 130 basis points are labeled as G-SIBs. For these banks, the allocation into buckets is made as follows. If its systemic score is between 130 and 230 basis points, the bank will be allocated to the first bucket and face an additional CET1 capital requirement (or "buffer") of 1 percent of its total risk-weighted assets. Next, buckets are then imposing more and more stringent buffers: 1.5 percent for banks with systemic scores between 230 and 330 bp, 2 percent between 330 and 430 bp, and 2.5 percent between 430 and 530 bp. Currently, the fifth and last bucket would

Figure B.1. Illustration of Current BCBS Methodology to Identify G-SIBs



trigger a 3.5 percent buffer if the systemic score were to reach the 530 bp threshold. For the time being, this last bucket is only "dissuasive" and has never been applied to any G-SIB.

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Chapter 3.

Lending by Private, Cooperative and State-owned Banks to Non-Financial Corporates over the Cycle: Does Bank Type Matter?

Aurélien VIOLON

Lending by Private, Cooperative and State-owned Banks to Non-Financial Corporates over the Cycle: Does Bank Type Matter?

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ABSTRACT:

This paper investigates the credit growth dynamics in the French banking sector and provides empirical evidence of asymmetries in credit supply across types of bank. We use a granular bank-firm-level panel over 84 quarters from 1991Q1 to 2019Q4 and measure the evolution of credit for each bank-firm relation. Then we apply an identification strategy based on the selection of "multi-bank-type" non-financial corporates to control for demand-side effects. Based on 276 banks and 13,125 firms, we show that private banks exhibit a procyclical credit supply behavior, while state-owned banks follow a countercyclical pattern. In between, cooperative banks appear less procyclical than private banks. We also show that during the most severe macroeconomic turmoil in the aftermath of the 2008 great financial crisis, cooperative banks reduced their credit supply much less than private banks, while state-owned banks did not react to this extreme shock. These findings have implications both at macro level for policy-makers concerned by the funding of the real economy in times of crisis and at micro level from a corporate finance perspective.

JEL classification: G01, G21, H81, E44

Keywords: Cooperative banks, state-owned banks, procyclicality, credit supply, bank-firm relations

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1 Introduction

The French banking sector is characterized by the presence of several types of bank. Some of them are private commercial banks listed on the stock market, while others are owned by a public entity (either by the State, municipalities or public agencies). The state-owned banking sector has experienced major changes in France over the past decade. Following the difficulties encountered by the French-Belgian banking group Dexia, its French subsidiary *Dexia Municipal Agency* was sold in January 2013 to the *Société de Financement Local* (SFIL), a bank mainly owned by the French government. The restructuring of this banking group pursued the objective of sustaining the financing of local authorities, which is the main line of activity of this banking group. During the same period, the *Banque Publique d'Investissement* (BPI) was created by a merger of several former state-related financing structures and guarantee schemes. Its mission was to strengthen the financing of French SMEs and midcaps. These two events illustrate the desire to reinforce the ability of state-related entities to finance the French economy, in a macroeconomic context that was characterized by low GDP growth and by a suspected credit rationing by private commercial banks. Then, the declared objective of these two state-owned banking groups is *"to play a countercyclical role in the financing of the economy and to address some market imperfections"* BPI [2013]. But the French banking system's other specificity is the presence of three major "cooperative" banking groups[1] that collectively account for more than half of all loans and deposits in France. Other national banking systems in Europe are also characterised by a significant market share of cooperative banks, such as Germany and Italy (cf. Egarius and Weill [2016] for instance). If cooperative banks are private institutions, in the sense that they do not belong to a state-related entity, they differ from private commercial banks because they are not listed

[1]The French law, in the "Code monétaire et financier" article L511-30, officially defines these three groups: *Groupe Crédit Agricole*, *Groupe Crédit Mutuel*, and *Groupe Banques Populaires Caisses d'Epargne - BPCE*

on the stock market[2] and their shareholders are actually some individual depositors of these banks who are called *"sociétaires"*. This variety of bank ownership may affect their respective credit supply policy over the economic cycle for several reasons.

From a theoretical perspective, we expect state-owned banks to have a less procyclical credit supply than private banks. Brei and Schclarek [2015] developed a model in which, in the event of a shock, state-owned banks lend more to economic agents during the crisis, while private banks tend to reduce their outstanding loans to favor the holding of more liquid assets. This asymmetrical behavior could theoretically be explained by three reasons. First, unlike private banks, state-owned banks would not only seek to maximize their profit, but would internalize the consequences of their lending on the stability of the economy. Second, they would be less exposed to funding problems[3] because they can benefit from the State's privileged access to capital markets. Finally, they are less likely than private banks to experience massive withdrawals of deposits (bank-runs) because they benefit more than private banks from the guarantee of the State and therefore appear more solvent from the depositors' point of view. Leony and Romeu [2011] introduces a model based on the idea that a state-owned bank is, all things equal, less exposed to ex-ante risk than a private bank. In times of crisis, when private banks have to recapitalize and reallocate their assets, state-owned banks are therefore in a better position to increase their outstanding loans to economic agents.

Using bank-level data, several papers found empirical evidence of such reduced procyclicality of credit from state-owned banks compared to private banks. In line with Micco and Panizza [2006] and Cull and Martinez Peria [2013], Brei and Schclarek [2013] showed that private banks actually tend to reduce their outstanding loans in periods of crisis while state-owned banks on the contrary increase their outstanding amounts during these periods, based on a sample of 764 banks spread across 50 countries from

[2]However a cooperative group may have some of its subsidiaries listed.

[3]The causal link between liquidity troubles at bank level and its subsequent negative consequences on credit distribution has also been documented by Cornett et al. [2011] and Rajkamal et al. [2014].

1994 to 2009. Also based on an international sample of banks, Bertay et al. [2015] finds that lending by state-owned banks is indeed less procyclical than lending by private banks, but especially in countries with good governance. Lending by state-owned banks is even countercyclical in high-income countries. From a national perspective, Leony and Romeu [2011] also reached results in the same line for the South Korean banking sector. For Germany, Behr et al. [2017] quantifies a 25% reduced procyclicality in lending by banks with a public mandate compared to other banks. Other papers using micro data corroborate these findings at firm-level. For instance, Jimenez et al. [2018] shows that loans by state-owned banks had a major social impact and that the use of state-owned banks in the context of an economic crisis can be seen as a countercyclical policy in the case of Spain. Similarly, based on Japanese data, Lin et al. [2012] brings empirical support to the idea that state-owned banks lending helps boosting investments at firm level during the crisis, and especially for the more credit-constrained firms.

If those papers tend to highlight the social benefits of lending by state-owned banks, other papers also warn against some drawbacks of the involvement of the State in the banking system. Cihak and Demirgüç-Kunt [2013] finds negative consequences of such substitution of state-owned banks' credit to private banks' credit: while they indicate that this countercyclical effect in the issuance of loans may have beneficial effects in the short term, they point out that the long-term impact of greater intervention by state-owned banks may be negative. They argue that state-owned banks' loans would be more subject to misallocation and low quality of intermediation compared to private banks. In the same line, Gadanecz et al. [2012] shows that state-owned banks tend to underestimate risk and use this privileged status only for competitive purposes to offer lower rates, but this would not benefit to the economy through innovative investments or corrections of true market failures in the banking sector, and Sapienza [2004] notices that state-owned banks generally have lower profitability in terms of return on assets and display larger non-performing loan ratios than other banks. Besides, Dinç [2005] and

Carvalho [2014] finds evidence that state-owned banks credit expansion is more prone to be influenced by the political agenda. However, Delatte et al. [2020] shows that political influence may as well affect private banks in the case of the French banking market. Similarly, Barry et al. [2016] finds that state-owned banks are generally more prone to lending corruption.

Regarding cooperative banks, the academic literature seems much less extended than for state-owned banks, with a few notable exceptions. Cihak and Hesse [2007] finds that cooperative banks are more stable than commercial banks due to a lower volatility of their returns. Therefore, the presence of cooperative banks contributes to better financial stability. Becchetti et al. [2016] reveals some differences in the characteristics of cooperative banks' balance sheet and earnings compared to other banks. A special issue of the *Revue d'Economie Financière* published in 2019 gathers several contributions about the French and European cooperative banks and mutual insurers. None of these references deals with the cyclicality of credit by cooperative banks. However, as pointed out notably by Roux [2019], cooperative banks have several characteristics and strengths that should make some differences with other commercial private banks. As mentioned by Boland and Barton [2013], the control of these cooperative entities is usually based on a "one member, one vote" principle and is not proportional to the number of shares hold by each "sociétaire". This specific status of equal client-shareholders is supposed to have a positive impact in terms of governance to reduce moral hazard and promote long-term relationship between the bank and its clients, especially in times of economic downturn. These cooperative banks are organized into groups structured around a "central body" that has a technical, administrative and financial control over all the group's affiliates. Since mutual financial assistance dispositions are enforceable between affiliates of a cooperative group, this should smooth shocks affecting some of these affiliates and help them maintaining their credit supply even in difficult times. Those three cooperative groups contain numerous regional banks that are called *"caisses"* that have a strong local

specialization and a deep long-term knowledge of all local economic agents. Their dense territorial presence should give these cooperative banks a better understanding of the intrinsic credit risk of their clients' projects. Moreover, as underlined by Becchetti et al. [2016] long-term relations with clients should reduce informational asymmetries between lenders and borrowers, thereby improving the quality of credit. Therefore, their credit supply is expected to be less driven by short-term economic conjuncture, but rather by long-term solvency of their clients. For all these reasons, we can expect the cooperative banks' credit supply to be less procyclical than in the case of commercial private banks that may be more focused on short-term performance and could react more strongly to the economic conjuncture.

Given this background and the existing literature, the purpose of this paper is twofold. First, we investigate the dynamics of credit to non-financial corporates in France to assess whether we can find empirical evidence of a reduced procyclicality of lending by state-owned French banks, as it is usually the case in the literature for international panels or some foreign national banking systems. Second, we split the French banking system into three types of bank: beyond the usual dichotomy between private and state-owned banks, we analyze separately cooperative banks to determine if their credit supply differs from other banks, since the academic literature does not already provide such insight, to the best of our knowledge. We use a database on credit to corporates in France at granular bank-firm level. Each bank-firm relation with a minimum of 76,000 euros of total loans is tracked over time quarterly in our dataset over the period 1999Q1-2019Q4. We apply a selection of "multi-bank-type" firms, meaning that we only keep firms that are permanently in credit relation with at least two types of bank (among state-owned, private and cooperative banks). Such restriction is crucial for our identification strategy, as it ensures that the demand for credit is homogeneous for all types of bank. Since demand-side effects are controlled for, we can identify supply-side effects in the regressions and assess whether we can find asymmetries in the credit supply

of each type of bank over the cycle. In our final unbalanced panel, we follow a total of 13,125 distinct firms and 276 distinct banks during these 21 years and we measure the evolution of credit at this granular level.

Based on 1,078,175 observations of credit growth at bank-firm level, we find empirical confirmation that credit supply to non-financial corporates in France by state-owned banks is less procyclical than in the case of private banks, and that it is even countercyclical. This first contribution corroborates the results usually seen in the literature, and especially those of Bertay et al. [2015]. We also show that, between state-owned and private banks, cooperative banks exhibit a reduced procyclicality of credit supply compared to private banks. This second contribution fills a gap in the existing literature and brings empirical support to the theoretical arguments exposed above, explaining that the cooperative banking sector differs from the private commercial banking sector in France in terms of credit supply behavior. These results are robust to alternative analyses performed at firm or bank level.

The remainder of this paper is organized as follows. Section 2 describes the constitution of the dataset and provides some descriptive statistics. Section 3 presents our econometric methodology. Sections 4 and 5 respectively show the econometric results and the robustness checks. Finally, section 6 concludes.

2 Constitution of the dataset and descriptive statistics

2.1 A granular dataset at bank-firm-level

We use granular data reported to the French central bank by all credit institutions located in France regarding their loans to firms. This "credit registry" database collects all amounts of loans at bank-firm level, as long as the credit exposure of the bank to the firm is greater than 76,000 euros[4].

[4]This reporting threshold has been lowered to 25,000 euros in 2006, but for consistency reasons over the full span of our panel, we kept constant this initial 76,000 euros threshold by excluding the smallest

In this database, the data is collected at *unconsolidated* level, which means that credit amounts and other variables are reported at solo level by each bank entity, and not at the highest level of consolidation of the banking group[5]. Since this data is collected at unconsolidated level, it only covers banks' activity in France, and to some minor extent abroad activities operated through branches. Banks' activities operated through foreign subsidiaries are not included, by construction. Therefore, the resulting panel almost only relates to banks' operations in France, which is precisely what we want to measure. Using this data source, we built a bank-firm-level unbalanced panel that covers the period 1999Q1-2019Q4 at quarterly frequency.

2.2 Bank type classification

In terms of bank selection, we only keep in our dataset banks that appear for at least 20 consecutive quarters for stability reasons[6]. All banks[7] in the dataset are then classified as either a "state-owned" bank, a "cooperative" bank, or a "private" bank.

"State-owned" banks are defined as credit institutions whose capital is mainly owned by a State or another state-related entity. We consider direct detention of banks' capital by a State or state-related entities, and a bank is classified as "state-owned" if and only if it is controlled (i.e. more than 50% of its capital is hold) by such owners.[8].

As explained in the introduction, the three cooperative banking groups are explicitly defined by the French law: *Groupe Crédit Agricole*, *Groupe Crédit Mutuel*, and *Groupe Banques Populaires Caisses d'Epargne - BPCE*. Therefore, we identify as "cooperative"

bank-firm relationships between 25,000 and 75,999 euros starting from 2006.

[5]For instance, we do not take into account the consolidated figures of the Groupe Crédit Agricole but the individual figures reported by each of its affiliates.

[6]Such filter is applied in order to avoid data gaps from some banks for which data would be missing just for a few quarters, which could distort our measure of credit growth. It only removes a tiny fraction of observations and does not affect the results: it does not introduce any "survival selection bias".

[7]Note that we paid a particular attention to bank mergers and acquisitions in order to keep comparable perimeters over time, as explained in details in appendix 1.

[8]Given this definition, BNP Paribas's largest shareholder may be the Belgian State, it is still considered as a private bank since States and state-related entities do not own more than 50% of BNP Paribas's capital.

banks each of their constituting entities (the *"caisses régionales"* as well as their central bodies and their subsidiaries).

Finally, all remaining entities that are neither state-owned nor part of a cooperative banking group are classified as "private" banks.

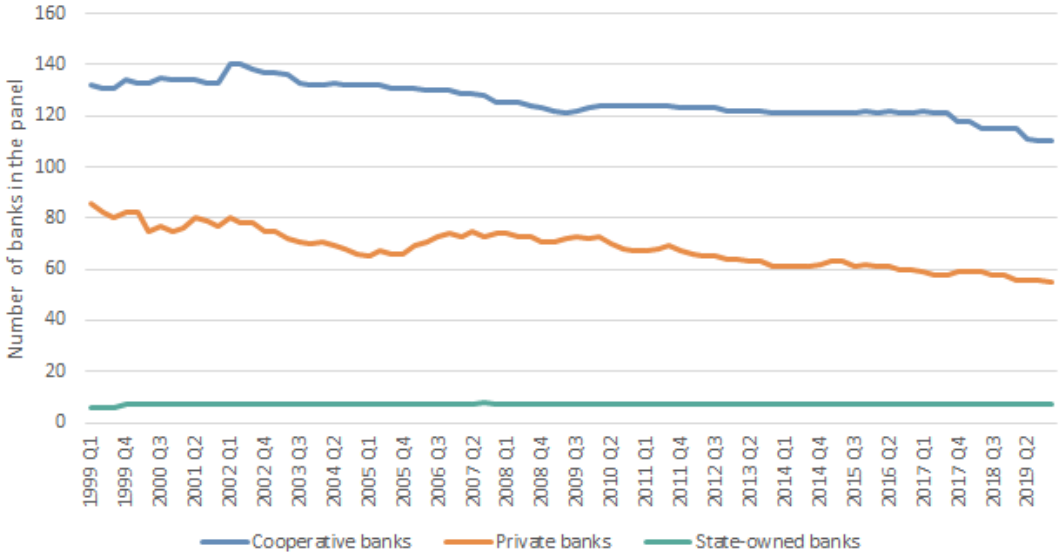

Figure 1: Number of banks by type over time

Our panel contains a total of 276 distinct banks[9] in the dataset over the full time-span, of which 121 are identified as private, 147 as cooperative and 8 as state-owned. The list provided in appendix 2 displays the names and classification of these 276 banks. On average, at each quarter, there are 201 active banks, with a maximum of 227 in 2002Q1 and a minimum of 172 in 2019Q4. Figure 1 shows how the number of each of these three types of bank has evolved over time. Among these 276 distinct banks, 67% of them actually belong to one of the six main French banking groups[10].

[9] By "bank" we mostly refer to entities with a "credit institution" license, in the sense of EU Directive 2010/76.

[10] Group Crédit Agricole, BNP Paribas, Société Générale, Group Banque Populaire Caisse d'Epargne (BPCE), Group Crédit Mutuel and La Banque Postale.

2.3 Selection of "multi-bank-type" firms

In terms of firm selection, we excluded firms involved in the financial industry to get a set of non-financial corporates located in France. Following a similar approach to the one used by Vinas [2016], we applied another key selection to this bank-firm-level dataset: we only keep firms that are *permanently* in credit relation with *at least two types of bank* (among state-owned, private and cooperative banks) over their entire recorded presence in our dataset. The selection of these "multi-bank-type" firms is crucial for the econometric identification strategy when using such bank-firm-level data, because it ensures that the "demand-side" is controlled for in the regressions. As in Khwaja and Mian [2008] and Vinas [2016], the underlying hypothesis is that firms that have structural links with several banks can easily apply for new credits to all of them. Therefore, we can consider credit demand to be homogeneous for all types of banks, and then we can infer that variations of credit come from the supply side.

Regarding non-financial firms considered in the final dataset, there is a total of 13,125 distinct firms over the full 1999-2019 time-span, with a maximum of 8,450 active firms in 2019Q4 and a minimum of 2,549 firms in 2005Q2. As shown in figure 2, over the full 1999-2019 time-span, cooperative banks account for an average of 51% of total credit granted to these multi-bank-type firms, while private and state-owned banks respectively represent 34% and 15% of credit[11].

Figure 3 compares time series of total loans to non-financial corporates (NFC) in France, in level on the left hand side and in growth rates on the right hand side. The black plain curve shows total loans to all NFC in France, as published each year by the French banking supervisory authority. It is by construction higher than the green dashed curve that shows total loans to NFC measured by the "credit registry", since smaller firms are not captured by this reporting. Finally, the green dotted curve shows total

[11] Note that even if the panel only contains 8 state-owned banks, they collectively account for roughly one sixth of total credit to these firms over the 1999-2019 period. Then it is relevant to identify them and treat them separately from private and cooperative banks in the following regressions.

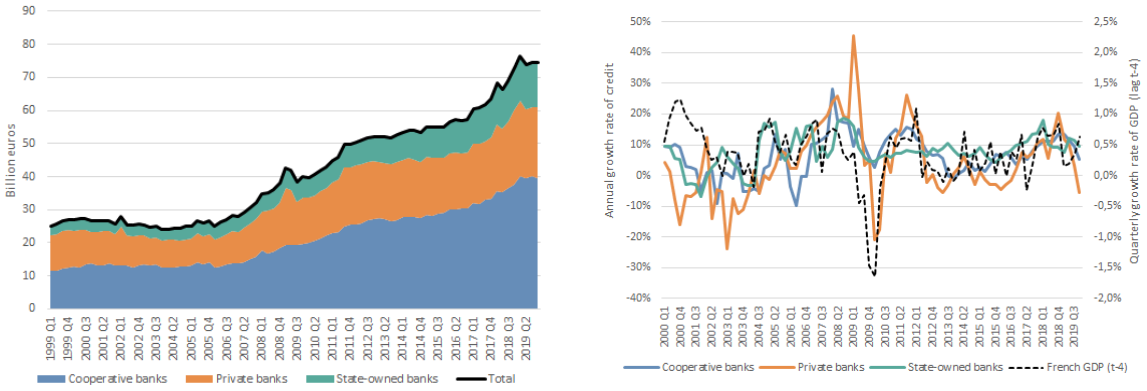

Figure 2: Breakdown of credit to "multi-bank-type" firms by type of bank (left: outstanding amounts / right: growth rates)

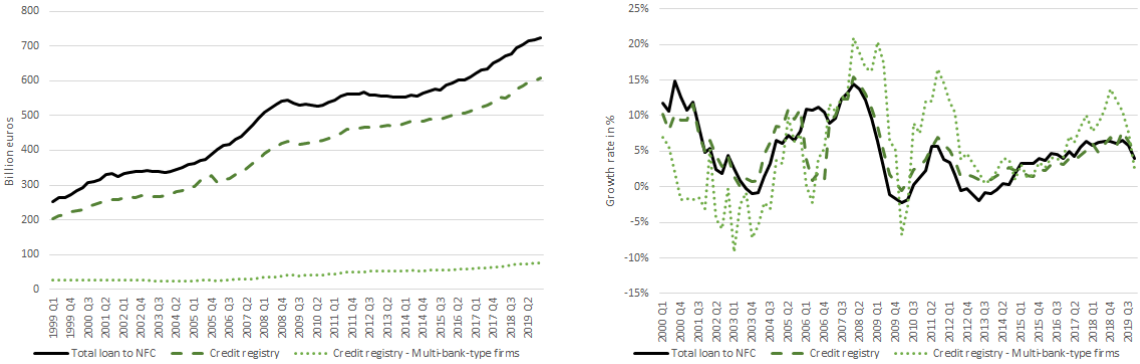

Figure 3: Loans to non-financial corporates in level (left) and in growth rates (right)

loans to our multi-bank-type firms, as defined above. Such selection obviously excludes a large amount of loans, but we notice that the three time series strongly commoves[12].

2.4 Measuring credit growth at bank-firm level

The core variable of our dataset is the amount of credit granted by a given bank to a given firm and its evolution over quarters. To measure this evolution, we compute what we refer to as the "mid-point growth rate" (or MPGR hereafter), as used by Beaumont et al. [2019] and put forward by Davis et al. [1996]. We define the MPGR of credit

[12]The correlation between total loans to all NFC and total loans in the credit registry equals 0.99, and the correlation between total loans in the credit registry and loans to "multi-bank-type" firms equals 0.96.

granted by bank B to firm F at quarter q as follows:

$$\Delta Credit_{B,F,q} = 2 * \frac{(Credit_{B,F,q} - Credit_{B,F,q-4})}{(Credit_{B,F,q} + Credit_{B,F,q-4})}$$

For small variations (positive or negative), the MPGR gives similar values as the more usual growth rate ($\frac{Credit_{B,F,q} - Credit_{B,F,q-4}}{Credit_{B,F,q-4}}$), but the major advantage of the MPGR is to avoid extreme values for new or terminating bank-firm relations. Indeed, for a new bank-firm relation, with $Credit_{B,F,q-4} = 0$ and $Credit_{B,F,q} > 0$ the usual growth rate would not be defined, while the MPGR equals 2. Conversely, if a bank-firm relation terminates at quarter q, with $Credit_{B,F,q-4} > 0$ and $Credit_{B,F,q} = 0$ the usual growth rate would take the value -100%, while the MPGR equals -2. Therefore the MPGR is well defined in all cases and varies between -2 and 2. Such precaution is not needed when using credit aggregates at bank-level (as they generally do not approach zero), but given the very high granularity of the dataset, the use of the MPGR appears necessary. The MPGR of credit at the bank-firm relation level will be our dependent variable in the main following regressions. Table 1 displays some key statistics of this MPGR of credit, for all time periods as well as in times of crisis or normal times (as defined in next subsection), and for our three types of bank. Overall, we have 1,078,175 observations of the MPGR of credit at the bank-firm level in our dataset over the period 1999Q1-2019Q4.

We notice that on average the MPGR of credit is negative for all types of bank and for all time periods. The fact that the mean of MPGR of credit is negative at bank-firm level is not inconsistent with the (generally) positive growth rate of aggregate credit to non-financial corporates. Indeed, we also notice in table 1 that for most observations (more than two thirds) the MPGR is negative with a mean equal to -24%, while for the third of observations with positive MPGR the mean is much higher to +38%. This is logical and illustrates that, since we measure the MPGR of credit at the bank-firm level,

		All times	Crisis times (C1)	Normal times	Crisis-Normal Difference	Positive MPGR	Negative MPGR
Coop.	Mean	-3.72%	-4.93%	-3.48%	-1.46 pp	38.55%	-24.90%
	Q1	-21.50%	-21.80%	-20.91%	-0.89 pp	7.82%	-30.34%
	Med.	-7.78%	-7.69%	-7.79%	0.10 pp	26.14%	-14.70%
	Q3	6.73%	5.60%	7.90%	-2.30 pp	57.50%	-7.60%
	N	574,772	97,945	476,827		186,837	387,935
	$B * \bar{F} * \bar{Q}$	147*167.8*23.3	147*167.8*4	147*167.8*19.3		147*167.8*7.6	147*167.8*15.7
Priv.	Mean	-5.10%	-6.71%	-4.66%	-2.50 pp	38.20%	-27.80%
	Q1	-24.35%	-25.63%	-24.90%	-1.54 pp	7.25%	-35.14%
	Med.	-8.34%	-8.56%	-8.30%	-0.26 pp	25.90%	-17.52%
	Q3	8.20%	5.11%	8.67%	-3.56 pp	56.81%	-8.51%
	N	353,682	59,875	293,807		119,925	233,757
	$B * \bar{F} * \bar{Q}$	121*129*22.7	121*129*3.8	121*129*18.8		121*129*7.7	121*129*15
S.O.	Mean	-4.55%	-3.91%	-4.68%	0.77 pp	37.89%	-16.42%
	Q1	-15.64%	-14.74%	-15.82%	1.80 pp	4.30%	-19.50%
	Med.	-8.50%	-7.64%	-8.14%	0.50 pp	22.97%	-10.36%
	Q3	-2.65%	-2.66%	-2.64%	-0.20 pp	58.60%	-6.67%
	N	149,721	24,540	125,181		32,712	117,009
	$B * \bar{F} * \bar{Q}$	8*811.3*23.1	8*811.3*3.8	8*811.3*19.3		8*811.3*5	8*811.3*18
Total	Mean	-4.26%	-5.38%	-4.30%	-1.35 pp	38.30%	-23.82%
	Q1	-21.16%	-21.82%	-21.50%	-0.77 pp	7.19%	-29.84%
	Med.	-7.99%	-7.91%	-8.00%	0.90 pp	25.81%	-14.55%
	Q3	4.81%	3.26%	5.15%	-1.89 pp	57.32%	-7.61%
	N	1,078,175	182,360	895,815		339,474	738,701
	$B * \bar{F} * \bar{Q}$	276*169.5*23.1	276*169.5*3.9	276*169.5*19.2		276*169.5*7.3	276*169.5*15.8

This table displays some summary statistics on our key variable of interest: the "mid-point growth rate" (MPGR) of credit measured at bank-firm level. It shows in rows the mean, 1st, 2nd and 3rd quartiles and the number of bank-firm-quarter observations N, for cooperative (Coop.), private (Priv.), state-owned (S.O.), and all (Total) banks. Statistics are based on 276 distinct banks (121 private, 147 cooperative and 8 state-owned) indicated as B in the table. $\bar{F}$ denotes the average number of firms per bank, and $\bar{Q}$ the average number of quarters per bank-firm relation. In columns, statistics are computed using all observations (All times), or differentiated between crisis times and normal times, using C1 criteria, as defined in section 2.5. Column "Crisis-Normal Difference" shows the difference between crisis and normal times. Columns "Positive MPGR" and "Negative MPGR" respectively show the statistics computed when the MPGR of credit is positive or negative. Using this "Crisis-Normal Difference" column, we perform Welch mean-difference t-test between bank types and we find a 1.0 pp difference between private and cooperative banks (p-value < 0.1) and a 3.3 pp difference between private and state-owned banks (p-value < 0.1).

Table 1: Summary statistics of mid-point growth rate (MPGR) of credit at bank-firm level

quarters where the firm is simply paying back its loans are more numerous than quarters where new loans granted by the bank increase the total amount of credit from bank B to firm F.

However, table 1 starts to reveal some interesting differences: in crisis times the MPGR of credit is lower than in normal times for both cooperative and private banks, but it is slightly higher for state-owned banks. The difference is also of smaller magnitude for cooperative banks compared to private banks. As a first insight in the data, this seems to indicate that in times of crisis the issuance of loans to non-financial corporates is less affected in the case of state-owned banks, and also to a smaller extent in the case of

cooperative banks, compared to private banks.

2.5 Macroeconomic variables

We collected several macroeconomic time series from the OECD's database. In order to measure the evolution of the issuance of credit "over the cycle", we retrieved the quarterly growth rate of the French GDP from 1999Q1 to 2019Q4. Over this period, France has known 15 quarters of negative growth rate of GDP, of which 4 were considered as a recession period (defined as at least two consecutive quarters with negative GDP growth rate) from 2008Q3 to 2009Q2. This key time series will be used in the regressions to define the economic cycle. Figure 4 provides a comparison of the economic and the credit cycles in France. Using a 4-quarter lag for GDP, and looking at 8-quarter moving averages, we notice a strong positive correlation of the two cycles, with a correlation coefficient of 0.57. This tends to show that, everything else equal, banks' credit growth reacts to past macroeconomic conditions.

Therefore, we define three "crisis variables":

- C1 is a dummy variable that takes value 1 if the 4-quarter lagged growth rate of GDP is negative, and 0 otherwise;
- C2 is a dummy variable that takes value 1 if the French economy was in recession 4 quarters ago, and 0 otherwise;
- C3 is the opposite of the growth rate of 4-quarter lagged GDP, therefore the higher the value of C3, the stronger the economic downturn.

Two other time series are collected to be used as macroeconomic control variables: the real short-term interest rate and the unemployment rate.

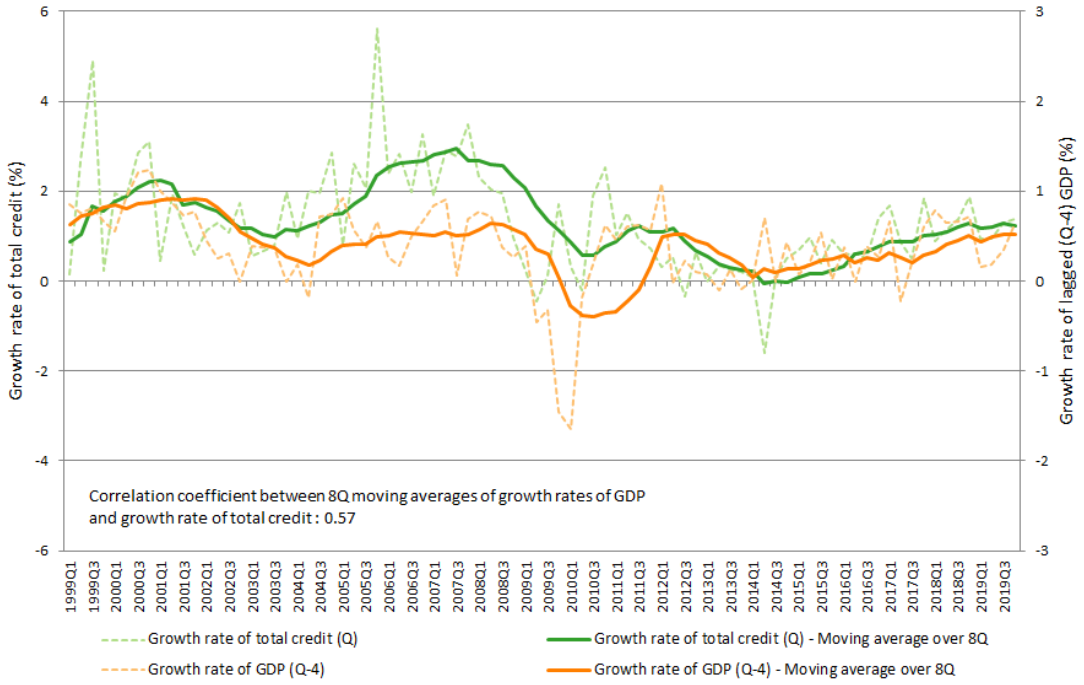

Figure 4: Quarterly growth rates of total credit in France and lagged GDP (4 quarters)

2.6 Banks characteristics

We also included usual bank-specific indicators to be used as control variables in the regressions. We include in this set of variables some balance sheet ratios that broadly capture banks' business model, such as the share of credit, securities and intra-bank assets within total assets, the share of deposits, securities issued and intra-bank liabilities within total liabilities. The equity over total asset ratio is a proxy of the Basel III leverage ratio that measures the capital adequacy of the bank. The efficiency of banks is measured by the cost efficiency ratio (cost eff), dividing operating expenditure by operating income. The profitability of banks is captured by the return on assets (ROA) and the return on equity (ROE). The size of banks is measured by the logarithm of total assets. Finally, the quality of the loan portfolio is taken into account with the share of non-performing loans (NPL). Table 2 provides the summary statistics for all these

bank-specific control variables, with a breakdown by type of bank (cooperative, private and state-owned).

		Credit /TA	Sec /TA	IBA /TA	Dep /TL	Sec /TL	IBL /TL	Equity /TA	Cost eff	ROA	ROE	Size	Share NPL
Coop.	Mean	15.38	67.37%	48.81%	5.75%	15.90%	38.55%	5.18%	40.53%	8.93%	52.12%	0.47%	3.11%
	Q1	14.39	57.29%	32.82%	0.27%	5.40%	20.52%	0.00%	17.51%	5.59%	39.64%	0.25%	1.50%
	Med.	15.84	72.17%	52.80%	4.53%	10.98%	31.40%	0.79%	42.32%	7.90%	48.13%	0.42%	2.70%
	Q3	16.50	80.17%	64.28%	8.14%	20.81%	63.92%	6.90%	60.43%	10.56%	59.90%	0.61%	3.34%
	N	10,575	10,575	10,575	10,575	10,575	10,575	10,575	10,575	10,575	10,574	10,487	10,302
	B	147	147	147	147	147	147	147	147	147	147	147	147
	$\bar{Q}$	71.9	71.9	71.9	71.9	71.9	71.9	71.9	71.9	71.9	71.9	71.3	70.1
Priv.	Mean	14.7	61.32%	43.68%	5.13%	13.51%	29.91%	5.86%	45.72%	9.34%	59.17%	0.60%	4.22%
	Q1	12.79	42.35%	17.93%	0.00%	2.92%	0.59%	0.00%	8.80%	4.67%	33.25%	0.23%	0.85%
	Med.	13.96	66.28%	43.93%	0.00%	9.24%	19.81%	0.00%	48.26%	7.14%	60.38%	0.53%	2.43%
	Q3	14.99	81.73%	66.79%	5.62%	19.22%	58.84%	6.88%	80.20%	10.76%	85.72%	0.93%	5.51%
	N	5,736	5,736	5,736	5,736	5,736	5,736	5,736	5,736	5,736	5,726	5,541	5,435
	B	121	121	121	121	121	121	121	121	121	121	121	121
	$\bar{Q}$	47.4	47.4	47.4	47.4	47.4	47.4	47.4	47.4	47.4	47.3	45.8	44.9
S.O.	Mean	16.34	50.99%	35.10%	13.68%	14.42%	11.25%	28.97%	30.99%	7.88%	76.38%	0.37%	2.10%
	Q1	14.68	21.22%	4.50%	5.26%	2.24%	0.30%	0.00%	8.70%	2.44%	63.50%	0.11%	0.10%
	Med.	16.63	51.55%	26.57%	12.15%	7.18%	1.72%	18.53%	26.19%	4.96%	81.37%	0.25%	1.19%
	Q3	18.9	79.80%	63.68%	21.70%	26.39%	8.48%	50.76%	56.37%	10.53%	96.23%	0.39%	3.59%
	N	586	586	586	586	586	586	586	586	586	586	583	581
	B	8	8	8	8	8	8	8	8	8	8	8	8
	$\bar{Q}$	73.3	73.3	73.3	73.3	73.3	73.3	73.3	73.3	73.3	73.3	72.9	72.6
Total	Mean	14.97	64.74%	46.59%	5.81%	15.40%	34.67%	6.24%	41.96%	9.30%	55.35%	0.51%	3.44%
	Q1	13.58	49.83%	24.83%	0.00%	4.41%	4.21%	0.00%	15.57%	5.12%	38.65%	0.24%	0.97%
	Med.	15.20	70.100%	50.41%	3.21%	10.43%	28.28%	0.44%	43.90%	7.57%	50.49%	0.44%	2.14%
	Q3	16.31	80.45%	64.72%	8.15%	20.40%	62.28%	6.82%	64.72%	10.60%	73.13%	0.68%	4.30%
	N	16,897	16,897	16,897	16,897	16,897	16,897	16,897	16,897	16,897	16,886	16,611	16,318
	B	276	276	276	276	276	276	276	276	276	276	276	276
	$\bar{Q}$	61.2	61.2	61.2	61.2	61.2	61.2	61.2	61.2	61.2	61.2	60.2	59.1

This table displays some summary statistics on our set of bank-specific control variables. It shows in rows the mean, 1st, 2nd and 3rd quartiles and the number of bank-quarter observations N, for cooperative (Coop.), private (Priv.), state-owned (S.O.), and all (Total) banks. Statistics are based on 276 distinct banks (121 private, 147 cooperative and 8 state-owned) denoted B. $\bar{Q}$ indicates the average number of quarters per bank. In columns, statistics are computed for each of our bank-specific control variables: share of total credit in total assets (Credit / TA), share of securities in total assets (Sec / TA), share of intra-bank assets in total assets (IBA / TA), share of deposits in total liabilities (Dep / TL), share of securities issued in total liabilities (Sec / TL), share of intra-bank liabilities in total liabilities (IBL / TL), the equity-to-asset ratio (Equity / TA), the cost efficiency ratio (Cost eff), the return on assets (ROA), the return on equity (ROE), the size of the bank (Size) measured as the logarithm of total assets, and the share of non-performing loans among total loans (Share NPL).

Table 2: Summary statistics on bank-specific control variables

In the bank dimension of our panel, figure 5 displays the concentration of bank on the market of loans to our multi-bank-type non-financial corporates. We can see that the largest bank in the sample accounts for roughtly 11% market share of total loans granted to these clients. The second largest bank represents around 10% of total loans, the third one 7%, and so on. Therefore, the French market of loans to these non-financial corporates shows a certain degree of concentration as big players account for significant market shares (the ten largest banks have a cumulative market share of approximately 50% over the whole time span of our panel), but this graph also illustrates that competition remains.

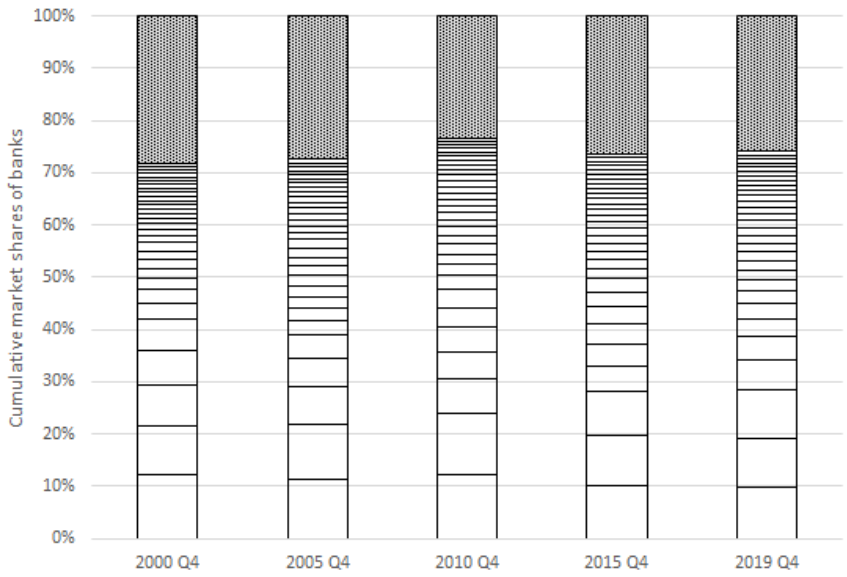

Figure 5: Bank contentration on the market of loans to multi-bank-type non-financial corporates

2.7 Firms characteristics

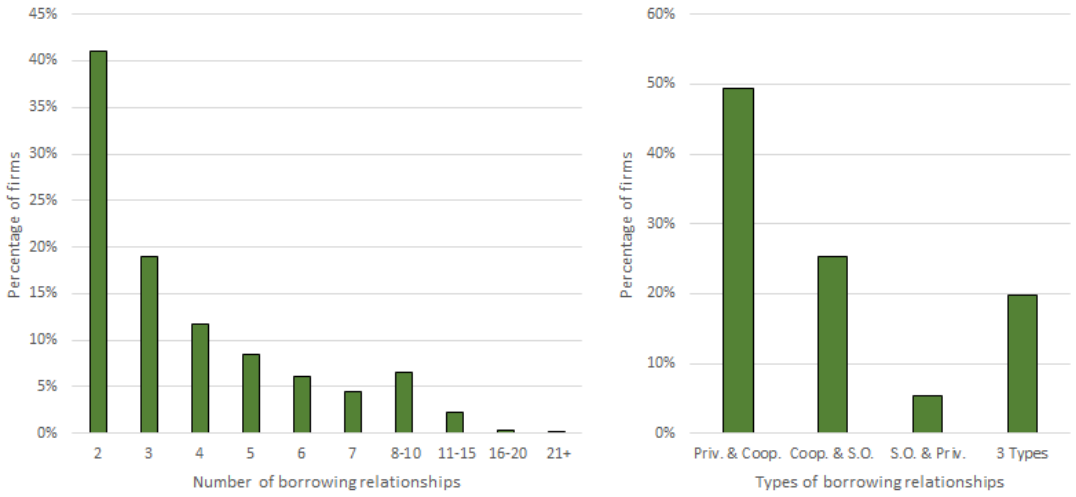

Figure 6: Distribution of number (left) and types (right) of bank relations per firm

In the firm dimension of our panel, figure 6 shows the distribution of the number of bank relations per firm. We notice that around 41% of firms in our sample have

relations with only two banks[13], 19% of firms have relations with 3 banks, 12% with 4 banks, 9% with 5, and then this percentage continues to regularly diminish as the number of bank relations increases. In terms of types of bank, 49% of firms in our panel borrow simultaneously from private (Priv.) and cooperative (Coop.) banks but not from state-owned (S.O.) banks, 25% solely from cooperative and state-owned banks, 5% solely from state-owned and private banks, while 20% of firms simultaneously borrow from all three types of bank.

We also included in our dataset three key features of these firms:

- Their sectoral classification that comprises 15 economic sectors. Figure 7 illustrates the repartition of credit between these sectors for both the full credit registry database and our sample of multi-bank-type firms. It appears that in our dataset, around 30% of total credit is granted to companies in real estate activities, 16% to manufacturing industry, 15% to retail and wholesale trade, while for instance agriculture and fishing companies represent less than 1% of total credit in our panel.

- Their rating scale used by the Banque de France to score the credit quality of firms in France. This scale goes by decreasing quality from "3++" down to "9", with "P" signaling firms in default. Note that more than 40% of the firms in our panel do not have a Banque de France credit rating.

- Their geographical location at *"département"* level[14] in order to take into account potential diverging credit situations across these regions.

These three characteristics of firms will be used as firm-specific control variables (dummies) in the regressions to take into account the potential heterogeneity of credit

[13]Note that no firm has a relation with a single bank since we restricted our sample to multi-bank-type firms.

[14]France is administratively devided into 100 geographical areas called "départements".

conditions across economic sectors[15], credit worthiness of firms, and geographical specificities.

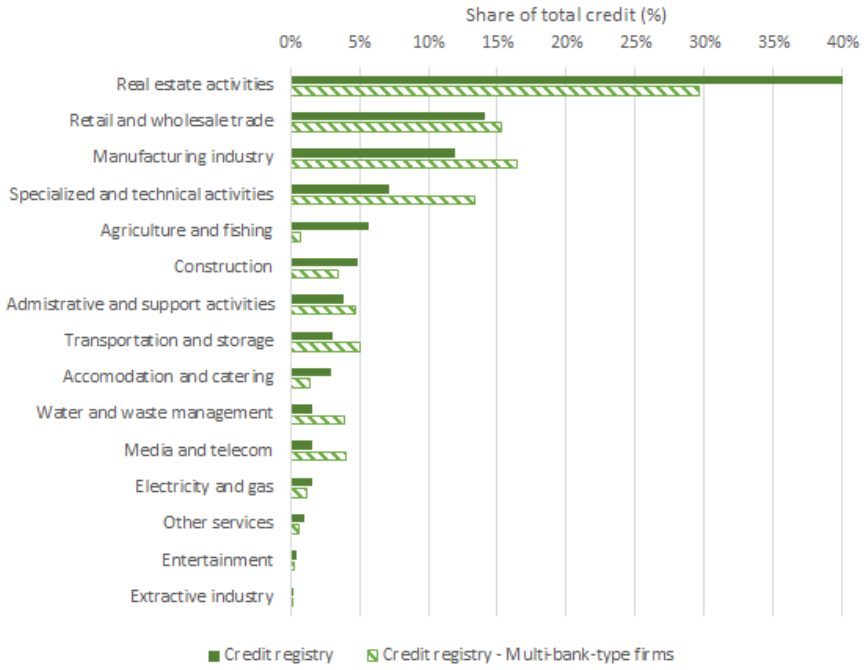

Figure 7: Sectoral repartition of credit

3 Econometric methodology

Building on the work of Brei and Schclarek [2013], we take inspiration from their econometric specification to measure the evolution of credit granted to non-financial corporates by our three types of bank, both during normal and crisis times, taking into account bank-specific characteristics, firm-specific characteristics and other aggregate macroeconomic conditions. Note that, as described above, the restriction of the dataset to "multi-bank-type" firms (i.e. that are permanently in credit relation with at least two

[15]Figure 7 presents a broad 15-sector decomposition of firms included in our panel, but for better accuracy the firm-specific control variables will use a more granular sectoral decomposition comprising around 70 different sub-sectors.

types of bank) improves our identification strategy. As such restriction helps controlling for demand-side effects, the potential asymmetries in the credit cycle of the three types of bank can more easily be interpreted as supply-side effects.

The dependent variable will be the growth rate of loans measured at bank-firm-level. On the right hand side of the equation we will use alternatively our three "crisis variable" (C1, C2 and C3), as defined in subsection 2.5. We also include two bank-type dummies, "SO" that indicates state-owned banks, and "COOP" that indicates cooperative banks (private banks levels will be measured as a "baseline" when both these dummy variables are equal to zero). The specification also includes two interaction terms between these bank-type dummies and the selected "crisis" variable. In some regressions, bank-specific and firm-specific control variables will be added, as well as dummies for quarters (to capture potential seasonality), and some changes in macroeconomic aggregates.

Our methodology can be summarized by the following equation:

$$\Delta Credit_{B,F,t} = \alpha + \alpha^*.Ck_t + (\alpha_{SO} + \alpha^*_{SO}.Ck_t).SO_B + (\alpha_{COOP} + \alpha^*_{COOP}.Ck_t).COOP_B +$$

$$\beta.BCV_{B,t-4} + \gamma.Q_t + \phi.M_{t-4} + \lambda.FCV_{F,t-4} + \epsilon_{B,F,t} \quad \text{, with } k \in \{1,2,3\} \qquad (1)$$

where $\Delta Credit_{B,F,t}$ denotes the mid-point growth rate (MPGR) of credit granted by bank B to firm F at time t, as defined in subsection 2.4. It measures the annual relative change of credit granted by bank B to firm F between $t-4$ and t. Ck_t is one of our three crisis variables, as defined in subsection 2.5. SO_B is a dummy variable taking value 1 when the bank B is state-owned, and zero otherwise. Similarly, $COOP_B$ is a dummy variable taking value 1 when the bank is cooperative. These two bank-dummy variables are also interacted with the crisis variable. $BCV_{B,t-4}$ is the set of bank-specific control variables, Q_t a set of quarterly dummies to capture seasonality, M_{t-4} a set of macroeconomic variables, $FCV_{F,t-4}$ the set of firm-specific control variables and $\epsilon_{B,F,t}$ the error term. The three sets of macroeconomic, bank-specific and firm-specific

control variables are lagged by 4 quarters in order to avoid any endogeneity issue that could be due to simultaneity. Our six key parameters of interest are α, α^*, α_{SO}, α^*_{SO}, α_{COOP} and α^*_{COOP}. Note that in order to facilitate the direct interpretation of these six coefficients, all variables of the sets $BCV_{B,t-4}$, Q_t, M_{t-4} and $FCV_{F,t-4}$ have been demeaned. Therefore, the six α-parameters can be read as the average annual credit growth rates in the average bank-firm relation.

In terms of interpretation, everything else equal, α will measure the average MPGR in a bank-firm relation in the case of private banks during "normal" times (i.e. non-crisis times). Coefficient α^* captures the potential deviation from α for private banks in times of crisis. It enables us to determine if (and if so, by how much) private banks reduce/increase credit growth in times of crisis. Parameters α_{SO} and α_{COOP} measure by how much the growth rate of credit structurally differs from the one of private banks respectively for state-owned and cooperative banks. And similarly, α^*_{SO} and α^*_{COOP} estimate, for these two types of bank, the deviation of their growth rate of credit in times of crisis compared to normal times.

To summarize, the average MPGR of credit at bank-firm level for the three types of bank during both types of period (normal and crisis times) should be computed as follows in table 3:

Average MPGR of credit	Normal times	Crisis times	Impact of crisis
Private banks	α	$\alpha + \alpha^*$	α^*
State-owned banks	$\alpha + \alpha_{SO}$	$\alpha + \alpha^* + \alpha_{SO} + \alpha^*_{SO}$	$\alpha^* + \alpha^*_{SO}$
Cooperative banks	$\alpha + \alpha_{COOP}$	$\alpha + \alpha^* + \alpha_{COOP} + \alpha^*_{COOP}$	$\alpha^* + \alpha^*_{COOP}$

Table 3: Average impact of crisis on the dependent variable

Hypothesis: Given the theoretical literature reviewed, we expect α^* to be negative and α^*_{SO} to be positive, meaning that in times of crisis private banks reduce their credit growth whereas state-owned banks tend to have less procyclical - or even countercyclical - credit supply. And given the specificities of the cooperative banks exposed in the introduction,

we would also expect to find a positive α^*_{COOP}.

4 Dynamics of credit to "multi-bank-type" firms

Table 8 displays the regression results of equation (1) using "C1" as crisis criteria (ie. taking value 1 if the quarterly growth rate of GDP was negative four quarters before). It shows five alternative regressions. In the first one, we only regress $Credit_{B,F,t}$ (the MPGR of credit granted by bank B to firm F) on the crisis variable, the bank-type dummies and their interaction terms, so that we only estimate our six key parameters of interest. In the second regression, we add the set of bank-level control variables to take into account the variety of situations each bank in the dataset can face. Regression (3) adds some quarterly dummies that aim to capture a potential seasonality of credit. On top of that, in regression (4) we also take into account national macroeconomic conditions by adding two macro-level control variables: the variation of real short-term interest rate, and variation of unemployment rate. Finally, for the most complete regression (5), we also add in the specification our set of firm-level control variables: some dummy variables for their credit score category, some sectoral dummies and geographical location dummies. Note that for the sake of brevity, the regression results for these sectoral and geographical dummies are not displayed in table 8 and subsequent regression tables. As a first general observation, we notice that all coefficients' magnitude, as well as their significance level, remain quite stable across these five alternative specifications.

Looking at coefficient α, we notice a negative sign in all five specifications, with a value equal to -8.3% in regression (5). This means that, everything else equal, at the bank-firm level, the amount of credit decreases on average by 8.3% each year for bank-firm relations in the case of private banks. Such negative growth rate of credit measured at the bank-firm level can seem surprising but is actually perfectly logical, as explained earlier in section 2. At such granular bank-firm relation level, there are much

more periods where the firm is repaying its loans than periods where the bank grants new credits to the firm. Hence, on average, the mid-point growth rate appears negative. Coefficient α^* is also negative and significant, which indicates that the MPGR of credit decreases by 0.9 percentage points in times of crisis for bank-firm relations in the case of private banks (still based on regression (5)). Coefficient α_{SO} is generally significantly negative, which means that on average the MPGR of credit for bank-firm relations in the case of state-owned banks is structurally lower than in the case of private banks[16]. However, since α^*_{COOP} and especially α^*_{SO} are positive and significant, we can infer that, in times of crisis, cooperative and state-owned banks reduce the supply of credit less than private banks compared to their respective policies in normal times. Table 4 summarizes the effect of crisis (as defined by our criteria "C1") on the mid-point growth rate of credit (MPGR) in the case of bank-firm relations by types of bank.

***Result n°1**: It appears that the annual growth rate of credit at bank-firm level is reduced by 0.9 percentage points (pp) in the case of private banks in time of crisis, while the reduction is less pronounced for cooperative banks (-0.4 pp). In contrast, in the case of bank-firm relations with state-owned banks, the growth rate of credit is even stronger during the crisis (+1.3 pp), which indicates that state-owned banks have a countercyclical reaction to the macroeconomic downturn in terms of credit supply to non-financial corporates.*

Average MPGR of credit	Normal times	Crisis times	Impact of crisis (C1)
Private banks	-8.3 % ***	-9.2 % ***	-0.9 pp ***
Cooperative banks	-8.4 % ***	-8.8 % ***	-0.4 pp **
State-owned banks	-11.0 % ***	-9.7 % ***	1.3 pp ***

Significance level (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$) of a Wald test testing difference from 0

Table 4: Average impact of crisis (C1) on the MPGR of credit to multi-bank-type non-financial corporates at bank-firm level

Coefficients of the set of bank-level control variables also bring interesting findings. We notice that everything else equal, the MPGR of credit at bank-firm level becomes

[16]This can be explained either by less frequent new loans at bank-firm level for this type of banks, and/or by shorter average maturity of loans resulting in relatively higher repayment rates.

slightly lower as banks are bigger as the coefficient of the (bank) size variable is negative. Conversely, the more a bank is specialized in credit (measured by the share of credit within its total assets), the higher the MPGR of credit[17]. We also note that the variable measuring the share of NPL within the loan portfolio of the bank has a strongly significant negative sign, indicating that banks with relatively poor quality of existing credits tend to have slower growth rate of credit at bank-firm level.

The quarterly dummy variables reveal a small but significant degree of seasonality. Compared to the first quarter of the year, the MPGR of credit at bank-firm level tends to increase slightly more during Q2 (by 0.1 pp), and less during Q3 and Q4 (-0.3 and -0.5 pp). As for macroeconomic control variables, an increase of the unemployment rate logically appears to reduce credit growth 4 quarters later. Finally, we can see a rather monotonic relation between the quality of the firm credit score and the average MPGR of credit. Indeed, compared to firms for which the credit score is unavailable, firms rated "3++" (the best possible credit score) have on average their MPGR of credit 4.5 percentage points higher. As the quality of the firm's credit score diminishes, the coefficient becomes significantly negative starting from score "5+" and the value of the coefficient becomes more and more negative as the score worsens. This shows logically that, everything else equal, as the creditworthiness of a firm decreases, it obtains new loans less often and/or the average maturity of its loans gets shorter, implying a higher repayment rate (hence a more negative MPGR of credit).

In table 9, we show the results of the same five specifications as in table 8 but using "C2" crisis criteria instead of "C1". Therefore, the measured effect of the "crisis" is more restrictive in this case as C2 only captures the worst macroeconomic turmoil that happened between 1999 and 2019: the 2008-2009 recession. Compared to table 8, the six α coefficients of interest displayed in table 9 reveal the same signs and significance level, but the magnitude of α^*, α^*_{SO} and α^*_{COOP} is much larger than with "C1" crisis criteria.

[17]Note that this relation is concave as the coefficient of the square of this variable is negative.

This indicates that crisis effects on lending behavior of banks noticed in previous table with "C1" crisis criteria are even stronger when we look at the most severe definition of the crisis. This is also very clear looking at table 5 that summarizes the effect of crisis as defined by our criteria "C2" on the mid-point growth rate of credit (MPGR).

Result n^{o}2: *When we restrict the "crisis" definition to the most severe macroeconomic turmoil of the 2008-2009 recession, we find that the effects noticed in result n^{o}1 are even reinforced. The annual growth rate of credit at bank-firm level is reduced by 3.3 percentage points (pp) in the case of private banks in time of recession, while the reduction is twice as less pronounced for cooperative banks (-1.6 pp). In contrast, in the case of bank-firm relations with state-owned banks, the growth rate of credit appears unaffected by the recession.*

Average MPGR of credit	Normal times	Crisis times	Impact of crisis (C2)
Private banks	-8.3 % ***	-11.7 % ***	-3.3 pp ***
Cooperative banks	-8.4 % ***	-10.0 % ***	-1.6 pp ***
State-owned banks	-10.8 % ***	-10.7 % ***	0.1 pp

Significance level (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$) of a Wald test testing difference from 0

Table 5: Average impact of crisis (C2) on the MPGR of credit to multi-bank-type non-financial corporates at bank-firm level

Finally, table 10 shows the econometric results when crisis criteria "C3" is applied. Contrary to "C1" and "C2", crisis criteria "C3" is not binary but continuous (as it measures the opposite of the growth rate of the 4-quarter lagged GDP), so its interpretation differs from the case of "C1" and "C2". However, we notice the six α coefficients remain with the same signs as described previously and highly significant. This implies that the conclusions drawn in results n^{o}1 and n^{o}2 remain valid all over the cycle.

Result n^{o}3: *Over the economic cycle, credit supply to non-financial corporates by private banks tends to be procyclical as it expands faster during booms and is more heavily affected by macroeconomic turbulences. In the case of cooperative banks, the credit supply also appears procyclical, but significantly less than in the case of private banks, while state-owned banks exhibit an acyclical credit supply.*

5 Robustness checks

5.1 Dynamics of credit at firm level

As an alternative approach to what we exposed in section 4, we can exploit our dataset at the aggregated firm level (and no longer at the most granular bank-firm level) and apply another econometric specification. In this subsection, we aggregate all loans received from every banks for each firm and then we compute the mid-point growth rate (MPGR) of credit at firm level. We also compute, for each firm, the share of credit granted by each of the three types of bank. We respectively label $MSSO$, $MSCOOP$ and $MSPRV$ these "market shares" of state-owned, cooperative and private banks, at firm level. Regarding bank characteristics (size, business model variables, ROA, etc.), we compute their weighted average at firm level to get a synthetic measure of the bank control variables.

Finally, we transform our previous equation (1) into the following equation (2) at firm level:

$$\Delta Credit_{F,t} = \alpha + \alpha^*.C3_t + (\alpha_{SO} + \alpha^*_{SO}.C3_t).MSSO_{F,t-4} + (\alpha_{COOP} + \alpha^*_{COOP}.C3_t).MSCOOP_{F,t-4} + \beta.WABCV_{F,t-4} + \gamma.Q_t + \phi.M_{t-4} + \lambda.FCV_{F,t-4} + \epsilon_{F,t} \quad (2)$$

where $\Delta Credit_{F,t}$ denotes the mid-point growth rate (MPGR) of all credits granted to firm F at time t. $C3_t$ is our third crisis (continuous) variable. $MSSO_{F,t-4}$ and $MSCOOP_{F,t-4}$ are the "market shares" at firm-level of state-owned and cooperative banks, as defined above, lagged by 4 quarters. These two variables are interacted with the crisis variable. $WABCV_{F,t-4}$ is the set of 4-quarter lagged weighted-average bank control variables, Q_t the set of quarterly dummies, M_{t-4} the set of lagged macroeconomic variables, $FCV_{F,t-4}$ the set of lagged firm-level control variables (which contains sectoral, creditworthiness and geographical dummies) and $\epsilon_{F,t}$ the error term. Our six key

parameters of interest are still α, α^*, α_{SO}, α^*_{SO}, α_{COOP} and α^*_{COOP}, although their interpretation is different compared to previous section as $MSSO_{F,t-4}$ and $MSCOOP_{F,t-4}$ are continuous contrary to $COOP_B$ and SO_B that were binary in the main regressions of the paper.

Looking at table 11, as α^*_{SO} and α^*_{COOP} are positive and significant, we find that, all over the cycle, the growth of credit will be less procyclical for firms that are more funded by state-owned and cooperative banks.

***Result n°4**: The dynamics of credit growth at firm level corroborates our previous results obtained at bank-firm level: at the aggregated firm level we also find empirical evidence that a larger share of funding received from state-owned and/or cooperative banks will tend to reduce the procyclicality of total credit received by the firm.*

5.2 Dynamics of credit at bank level

In order to perform other robustness checks, we take advantage of another database. We use less granular data reported at bank-level by all credit institutions located in France to the *Autorité de contrôle prudentiel et de résolution*, the French prudential authority. We built an unbalanced panel at quarterly frequency that covers the period 1993Q1-2019Q4 and comprises on average 273 institutions per quarter (with a maximum of 337 in 1997Q4 and a minimum of 213 in 2019Q4). The drawback of this alternative less granular dataset is that it does not enable to apply the multi-bank-type identification strategy and then it cannot distinguish whether asymmetries in credit cycles between the three types of bank come from demand-side or supply-side effects. However, the coverage of this dataset is much larger, as it does not only concern corporates, but also other types of borrower such as households and public administrations. Therefore, applying a similar approach to this dataset as the one described in section 3 could bring us a generalization of our results for a larger scope of borrowers.

Since the data is now measured at bank level, the econometric specification described

in equation (1) needs to be adapted as follows:

$$\Delta L_{i,t} = \alpha + \alpha^*.Ck_t + (\alpha_{PUB} + \alpha^*_{PUB}.Ck_t).PUB_i + (\alpha_{COOP} + \alpha^*_{COOP}.Ck_t).COOP_i +$$

$$\beta.BCV_{i,t-4} + \gamma.Q_t + \chi.\Delta L_{i,t-4} + \phi.M_{t-4} + \epsilon_{i,t} \quad , \text{with } k \in \{1,2,3\} \tag{3}$$

where $\Delta L_{i,t}$ denotes the annual growth rate of credit granted by bank i between $t-4$ and t, and $\Delta L_{i,t-4}$ its 4-quarter lag, $BCV_{i,t-4}$ is the same set of lagged bank-specific control variables as used in previous sections, Q_t the set of quarterly dummies and M_{t-4} the set of macroeconomic variables. Our six key parameters of interest are still α, α^*, α_{PUB}, α^*_{PUB}, α_{COOP} and α^*_{COOP}, and their interpretation remains the same as previously, except that now it is measured at the aggregated bank level.

Note that the endogeneity of the lagged dependent variable $\Delta L_{i,t-4}$ may create estimation bias. However, given the large number of time periods in this panel, this bias is expected to be small[18]. To avoid this potential bias, one could apply the generalized method of moments (GMM) or System GMM estimators, but given the depth of the time dimension of this alternative panel that contains more than 100 periods, there is a major risk of "weak instruments proliferation" (see for instance Fajeau [2021]). This is why, in the spirit of Anderson and Hsiao [1982] and Chatelain and Ralf [2021], we chose to use a more parsimonious instrumentation scheme and simply use an IV regression with $L_{i,t-8}$ as instrument for the lagged dependent variable $\Delta L_{i,t-4}$. All other regressors are simply lagged by four quarters, still in order to reduce potential endogeneity bias.

The results of this bank-level regression are displayed in table 12 for the three crisis criteria C1, C2 and C3. Similarly to what we found at bank-firm level, we get a negative and significant coefficient α^* and positive and significant coefficients α^*_{SO} and α^*_{COOP} for the two binary crisis criteria C1 and C2. For these two criteria, tables 6 and 7 summarize the impact of crisis on the annual growth rate of credit for each type of bank, at the

[18] As shown by Nickell [1981] this bias tends to zero as the number of periods goes to infinity.

aggregated bank level. Looking at the results with our continuous criteria C3, we find the same results all over the cycle.

***Result n°5**: Looking at total credit issued to all types of borrowers at bank level, we show that the issuance of credit by state-owned and cooperative banks is less procyclical than in the case of private banks. This is the case for our three crisis criteria, meaning this is the case in the aftermath of an economic downturn, during a recession and even all over the cycle. This is in line with our previous results obtained at bank-firm level.*

Average annual growth rate of credit	Normal times	Crisis times	Impact of crisis (C1)
Private banks	5.3 % ***	-1.1 %	-6.2 pp ***
Cooperative banks	7.5 % ***	4.8 % ***	-2.7 pp ***
State-owned banks	0.9 %	2.4 %	1.5 pp

Significance level (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$) of a Wald test testing difference from 0

Table 6: Average impact of negative GDP growth on bank-level credit growth

Average annual growth rate of credit	Normal times	Crisis times	Impact of crisis (C2)
Private banks	4.8 % ***	-4.2 % **	-9.0 pp ***
Cooperative banks	7.4 % ***	3.0 % ***	-4.4 pp ***
State-owned banks	1.0 %	1.8 %	0.8 pp

Significance level (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$) of a Wald test testing difference from 0

Table 7: Average impact of recession on bank-level credit growth

6 Concluding remarks

This empirical paper uses a granular bank-firm-level panel to assess whether we can find differences in credit dynamics between private, state-owned and cooperative banks over the economic cycle. Our dataset focuses on credit to non-financial corporates in France at quarterly frequency over 21 years from 1999Q1 to 2019Q4. We rely on an identification strategy based on the restriction of this large dataset to "multi-bank-type" firms,

meaning firms that are structurally in a borrowing relationship with at least two banks from different types. This restriction ensures that demand-side effects are controlled for, which enables to identify supply-side effects in the variation of credit over the economic cycle.

Our findings reveal that the issuance of credit to non-financial corporates by private banks is reduced when macroeconomic conditions deteriorates, showing a procyclical behavior of their credit allocation. In comparison, cooperative banks show a less procyclical pattern, while state-owned banks even follow a countercyclical pattern. We also show that the procyclical allocation of credit for private and cooperative banks was even reinforced during the most severe economic turmoil that occured during the time span of our dataset: the 2008-2009 recession. In contrast, state-owned banks did not seem to have reacted to this shock in terms of credit supply.

Those results are corroborated when we analyze the dynamics of credit at more aggregated firm-level and bank-level: we find some empirical evidence that private banks tend to substantially reduce their credit growth following an economic downturn, while state-owned banks' credit provision does not seem to react to such economic crisis episodes. In between, cooperative banks reduce significantly their growth rate of credit in times of crisis, but much less than private banks and then appear to behave less procyclically.

In terms of implications, the contribution of this paper is twofold. From a macroeconomic level and with the goal to foster a sound funding of the real economy, being aware of such asymmetries in the long-run across these types of bank can be useful for policy-makers to set-up proper measures to avoid credit rationing in times of severe economic turmoil. Besides, from a microeconomic level and a corporate finance perspective, it highlights the relevance for a firm to diversify its funding sources and the interest to

build banking relationships with several types of bank that may follow different credit supply patterns over the cycle.

On the one hand, if theoretical reasons for the reduced procyclicality of state-owned banks' credit have been explored by the academic literature and have been backed by several empiral papers, including this one, on the other hand, further investigations whould be needed to fully explore the reasons of the reduced procyclicality of cooperative banks' credit that we elicited in this paper. This is left for future research.

Dependent variable: mid-point growth rate (MPGR) of credit at bank-firm level ($\Delta Credit_{B,F,t}$)					
Specification	(1)	(2)	(3)	(4)	(5)
Intercept (α)	-0.064***	-0.083***	-0.083***	-0.085***	-0.083***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
C1 (α^*)	-0.020***	-0.017***	-0.019***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
SO (α_{SO})	0.022***	-0.031***	-0.030***	-0.028***	-0.027***
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
C1*SO (α^*_{SO})	0.031***	0.024***	0.024***	0.023***	0.023***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
COOP (α_{COOP})	0.018***	-0.002	-0.002	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
C1*COOP (α^*_{COOP})	0.007**	0.006**	0.006**	0.006*	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Size (bank) - lag t-4		-0.007***	-0.007***	-0.006***	-0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
Credit / TA (bank) - lag t-4		0.217***	0.219***	0.218***	0.212***
		(0.038)	(0.038)	(0.038)	(0.038)
(Credit / TA)^2 (bank) - lag t-4		-0.108***	-0.110***	-0.105***	-0.105***
		(0.029)	(0.029)	(0.029)	(0.029)
Sec / TA (bank) - lag t-4		0.134***	0.135***	0.135***	0.128***
		(0.020)	(0.020)	(0.020)	(0.020)
IBA / TA (bank) - lag t-4		0.206***	0.207***	0.205***	0.189***
		(0.019)	(0.019)	(0.019)	(0.019)
Dep / TL (bank) - lag t-4		-0.139***	-0.137***	-0.130***	-0.128***
		(0.016)	(0.016)	(0.016)	(0.016)
Sec / TL (bank) - lag t-4		-0.106***	-0.107***	-0.107***	-0.106***
		(0.017)	(0.017)	(0.017)	(0.017)
IBL / TL (bank) - lag t-4		-0.141***	-0.141***	-0.134***	-0.131***
		(0.016)	(0.016)	(0.016)	(0.016)
Equity / TA (bank) - lag t-4		-0.203***	-0.204***	-0.177***	-0.169***
		(0.037)	(0.037)	(0.037)	(0.037)
Cost eff (bank) - lag t-4		-0.034***	-0.031***	-0.021**	-0.023***
		(0.009)	(0.009)	(0.009)	(0.009)
ROA (bank) - lag t-4		-0.188	-0.049	0.040	0.031
		(0.223)	(0.229)	(0.230)	(0.229)
Share NPL (bank) - lag t-4		-0.579***	-0.577***	-0.589***	-0.556***
		(0.050)	(0.050)	(0.050)	(0.049)
1_{Q2}			0.003***	0.001	0.001**
			(0.001)	(0.001)	(0.001)
1_{Q3}			-0.003***	-0.004***	-0.003***
			(0.000)	(0.001)	(0.001)
1_{Q4}			-0.005***	-0.006***	-0.005***
			(0.001)	(0.001)	(0.001)
Var unem (lag t-4)				-0.044***	-0.042***
				(0.003)	(0.003)
Var rstir (lag t-4)				0.002*	0.002
				(0.001)	(0.001)
Credit score 3++ (lag t-4)					0.045***
					(0.012)
Credit score 3+ (lag t-4)					0.042***
					(0.006)
Credit score 3 (lag t-4)					0.046***
					(0.004)
Credit score 4+ (lag t-4)					0.017***
					(0.004)
Credit score 4 (lag t-4)					0.001
					(0.003)
Credit score 5+ (lag t-4)					-0.033***
					(0.003)
Credit score 5 (lag t-4)					-0.016***
					(0.003)
Credit score 6 (lag t-4)					-0.026***
					(0.004)
Credit score 7 (lag t-4)					-0.050***
					(0.013)
Credit score 8 (lag t-4)					-0.063***
					(0.012)
Credit score 9 (lag t-4)					-0.075***
					(0.023)
Credit score P (lag t-4)					0.015***
					(0.005)
Obs. (bank-firm-quarter)	1,078,175	872,340	872,340	872,340	872,340
Bank-level control var.	NO	YES	YES	YES	YES
Quarterly dummies	NO	NO	YES	YES	YES
Macroeconomic control var.	NO	NO	NO	YES	YES
Firm-level control var.	NO	NO	NO	NO	YES

Random effect (RE) estimations with robust standard errors clustered at firm level. Regressions based on a bank-firm level quarterly panel with 276 distinct banks (121 private, 147 cooperative and 8 state-owned). Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. The set of bank-level control variables contains all variables described in subsection 2.6, macroeconomic control variables contain the variations of unemployment rate (Var unem) and or real short term interest rate (Var rstir). As described in subsection 2.7, firm-level control variables contain credit worthiness dummies, as well as sectoral and geographical dummies (not shown in the table for the sake of brevity). Our first crisis criteria C1 is a dummy variable that takes value 1 if the (4-quarter lagged) growth rate of GDP is negative, and 0 otherwise.

Table 8: Bank-firm level regression results using "C1" crisis criteria

Dependent variable: mid-point growth rate (MPGR) of credit at bank-firm level ($\Delta Credit_{B,F,t}$)					
Specification	(1)	(2)	(3)	(4)	(5)
Intercept (α)	-0.066***	-0.084***	-0.084***	-0.085***	-0.083***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
C2 (α^*)	-0.037***	-0.050***	-0.050***	-0.032***	-0.033***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
SO (α_{SO})	0.026***	-0.029***	-0.028***	-0.026***	-0.025***
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
C2*SO (α^*_{SO})	0.042***	0.035***	0.035***	0.035***	0.035***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
COOP (α_{COOP})	0.019***	-0.002	-0.002	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
C2*COOP (α^*_{COOP})	0.014*	0.018**	0.018**	0.018**	0.018**
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Size (bank) - lag t-4		-0.007***	-0.007***	-0.006***	-0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
Credit / TA (bank) - lag t-4		0.222***	0.223***	0.221***	0.216***
		(0.038)	(0.038)	(0.038)	(0.038)
(Credit / TA)^2 (bank) - lag t-4		-0.112***	-0.112***	-0.109***	-0.109***
		(0.029)	(0.029)	(0.029)	(0.029)
Sec / TA (bank) - lag t-4		0.137***	0.138***	0.135***	0.129***
		(0.020)	(0.020)	(0.020)	(0.020)
IBA / TA (bank) - lag t-4		0.204***	0.204***	0.202***	0.187***
		(0.019)	(0.019)	(0.019)	(0.019)
Dep / TL (bank) - lag t-4		-0.142***	-0.139***	-0.133***	-0.131***
		(0.016)	(0.016)	(0.016)	(0.016)
Sec / TL (bank) - lag t-4		-0.111***	-0.111***	-0.110***	-0.109***
		(0.017)	(0.017)	(0.017)	(0.017)
IBL / TL (bank) - lag t-4		-0.144***	-0.142***	-0.136***	-0.133***
		(0.016)	(0.016)	(0.016)	(0.016)
Equity / TA (bank) - lag t-4		-0.207***	-0.207***	-0.185***	-0.178***
		(0.038)	(0.038)	(0.037)	(0.037)
Cost eff (bank) - lag t-4		-0.034***	-0.031***	-0.023***	-0.024***
		(0.009)	(0.009)	(0.009)	(0.009)
ROA (bank) - lag t-4		-0.071	0.033	0.075	0.070
		(0.223)	(0.229)	(0.230)	(0.229)
Share NPL (bank) - lag t-4		-0.654***	-0.653***	-0.626***	-0.597***
		(0.051)	(0.051)	(0.051)	(0.050)
1_{Q2}			-0.001	-0.000	0.000
			(0.000)	(0.001)	(0.001)
1_{Q3}			-0.004***	-0.004***	-0.004***
			(0.000)	(0.001)	(0.001)
1_{Q4}			-0.007***	-0.006***	-0.006***
			(0.001)	(0.001)	(0.001)
Var unem (lag t-4)				-0.038***	-0.035***
				(0.003)	(0.003)
Var rstir (lag t-4)				0.003**	0.002*
				(0.001)	(0.001)
Credit score 3++ (lag t-4)					0.045***
					(0.012)
Credit score 3+ (lag t-4)					0.042***
					(0.006)
Credit score 3 (lag t-4)					0.046***
					(0.004)
Credit score 4+ (lag t-4)					0.017***
					(0.004)
Credit score 4 (lag t-4)					0.000
					(0.003)
Credit score 5+ (lag t-4)					-0.033***
					(0.003)
Credit score 5 (lag t-4)					-0.017***
					(0.003)
Credit score 6 (lag t-4)					-0.026***
					(0.004)
Credit score 7 (lag t-4)					-0.051***
					(0.013)
Credit score 8 (lag t-4)					-0.063***
					(0.012)
Credit score 9 (lag t-4)					-0.073***
					(0.023)
Credit score P (lag t-4)					0.015***
					(0.005)
Obs. (bank-firm-quarter)	1,078,175	872,340	872,340	872,340	872,340
Bank-level control var.	NO	YES	YES	YES	YES
Quarterly dummies	NO	NO	YES	YES	YES
Macroeconomic control var.	NO	NO	NO	YES	YES
Firm-level control var.	NO	NO	NO	NO	YES

Random effect (RE) estimations with robust standard errors clustered at firm level. Regressions based on a bank-firm level quarterly panel with 276 distinct banks (121 private, 147 cooperative and 8 state-owned). Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. The set of bank-level control variables contains all variables described in subsection 2.6, macroeconomic control variables contain the variations of unemployment rate (Var unem) and or real short term interest rate (Var rstir). As described in subsection 2.7, firm-level control variables contain credit worthiness dummies, as well as sectoral and geographical dummies (not shown in the table for the sake of brevity). Our second crisis criteria C2 is a dummy variable that takes value 1 if the French economy was in recession 4 quarters ago, and 0 otherwise.

Table 9: Bank-firm level regression results using "C2" crisis criteria

Dependent variable: mid-point growth rate (MPGR) of credit at bank-firm level ($\Delta Credit_{B,F,t}$)					
Specification	(1)	(2)	(3)	(4)	(5)
Intercept (α)	-0.084***	-0.098***	-0.098***	-0.095***	-0.093***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
C3 (α^*)	-0.041***	-0.030***	-0.030***	-0.021***	-0.021***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
SO (α_{SO})	0.045***	-0.014**	-0.013*	-0.013*	-0.012*
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
C3*SO (α^*_{SO})	0.044***	0.031***	0.031***	0.030***	0.030***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
COOP (α_{COOP})	0.025***	0.005	0.005	0.005	0.005
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
C3*COOP (α^*_{COOP})	0.013***	0.012***	0.012***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Size (bank) - lag t-4		-0.007***	-0.006***	-0.006***	-0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
Credit / TA (bank) - lag t-4		0.203***	0.205***	0.207***	0.201***
		(0.038)	(0.038)	(0.038)	(0.038)
(Credit / TA)^2 (bank) - lag t-4		-0.100***	-0.101***	-0.099***	-0.099***
		(0.029)	(0.029)	(0.029)	(0.029)
Sec / TA (bank) - lag t-4		0.126***	0.126***	0.129***	0.122***
		(0.020)	(0.020)	(0.020)	(0.020)
IBA / TA (bank) - lag t-4		0.196***	0.196***	0.198***	0.183***
		(0.019)	(0.019)	(0.019)	(0.019)
Dep / TL (bank) - lag t-4		-0.133***	-0.130***	-0.128***	-0.126***
		(0.016)	(0.016)	(0.016)	(0.016)
Sec / TL (bank) - lag t-4		-0.099***	-0.100***	-0.101***	-0.100***
		(0.017)	(0.017)	(0.017)	(0.017)
IBL / TL (bank) - lag t-4		-0.136***	-0.135***	-0.132***	-0.129***
		(0.016)	(0.016)	(0.016)	(0.016)
Equity / TA (bank) - lag t-4		-0.199***	-0.199***	-0.182***	-0.175***
		(0.037)	(0.037)	(0.037)	(0.037)
Cost eff (bank) - lag t-4		-0.031***	-0.028***	-0.022**	-0.023***
		(0.009)	(0.009)	(0.009)	(0.009)
ROA (bank) - lag t-4		-0.070	0.064	0.096	0.090
		(0.223)	(0.229)	(0.229)	(0.229)
Share NPL (bank) - lag t-4		-0.570***	-0.569***	-0.579***	-0.546***
		(0.050)	(0.050)	(0.050)	(0.049)
1_{Q2}			0.002***	0.001**	0.002***
			(0.001)	(0.001)	(0.001)
1_{Q3}			-0.003***	-0.003***	-0.003***
			(0.000)	(0.001)	(0.001)
1_{Q4}			-0.006***	-0.006***	-0.005***
			(0.001)	(0.001)	(0.001)
Var unem (lag t-4)				-0.034***	-0.032***
				(0.003)	(0.003)
Var rstir (lag t-4)				0.001	0.001
				(0.001)	(0.001)
Credit score 3++ (lag t-4)					0.046***
					(0.012)
Credit score 3+ (lag t-4)					0.043***
					(0.006)
Credit score 3 (lag t-4)					0.046***
					(0.004)
Credit score 4+ (lag t-4)					0.017***
					(0.004)
Credit score 4 (lag t-4)					0.001
					(0.003)
Credit score 5+ (lag t-4)					-0.033***
					(0.003)
Credit score 5 (lag t-4)					-0.017***
					(0.003)
Credit score 6 (lag t-4)					-0.026***
					(0.004)
Credit score 7 (lag t-4)					-0.051***
					(0.013)
Credit score 8 (lag t-4)					-0.063***
					(0.012)
Credit score 9 (lag t-4)					-0.072***
					(0.023)
Credit score P (lag t-4)					0.015***
					(0.005)
Obs. (bank-firm-quarter)	1,078,175	872,340	872,340	872,340	872,340
Bank-level control var.	NO	YES	YES	YES	YES
Quarterly dummies	NO	NO	YES	YES	YES
Macroeconomic control var.	NO	NO	NO	YES	YES
Firm-level control var.	NO	NO	NO	NO	YES

Random effect (RE) estimations with robust standard errors clustered at firm level. Regressions based on a bank-firm level quarterly panel with 276 distinct banks (121 private, 147 cooperative and 8 state-owned). Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. The set of bank-level control variables contains all variables described in subsection 2.6, macroeconomic control variables contain the variations of unemployment rate (Var unem) and or real short term interest rate (Var rstir). As described in subsection 2.7, firm-level control variables contain credit worthiness dummies, as well as sectoral and geographical dummies (not shown in the table for the sake of brevity). Our third crisis criteria C3 is the opposite of the growth rate of (4-quarter lagged) GDP.

Table 10: Bank-firm level regression results using "C3" crisis criteria

Dependent variable: mid-point growth rate (MPGR) of credit at firm level ($\Delta Credit_{F,t}$)					
Specification	(1)	(2)	(3)	(4)	(5)
Intercept (α)	-0.019**	0.026	-0.019	-0.031	-0.014
	(0.008)	(0.075)	(0.076)	(0.076)	(0.075)
C3 (α^*)	-0.052***	-0.051***	-0.052***	-0.044***	-0.042***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$MSSO_{t-4}$ (α_{SO})	0.096***	0.040*	0.044**	0.044**	0.064***
	(0.013)	(0.021)	(0.021)	(0.021)	(0.021)
C3*$MSSO_{t-4}$ (α^*_{SO})	0.083***	0.069***	0.069***	0.068***	0.065***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$MSCOOP_{t-4}$ (α_{COOP})	-0.059***	-0.030*	-0.029*	-0.029*	-0.020
	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)
C3*$MSCOOP_{t-4}$ (α^*_{COOP})	0.028**	0.024**	0.023**	0.023**	0.020*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Size (bank w.a.) - lag t-4		-0.017***	-0.016***	-0.015***	-0.015***
		(0.003)	(0.003)	(0.003)	(0.003)
Credit / TA (bank w.a.) - lag t-4		0.720***	0.731***	0.729***	0.646***
		(0.099)	(0.098)	(0.098)	(0.097)
(Credit / TA)^2 (bank w.a.) - lag t-4		-0.607***	-0.614***	-0.610***	-0.552***
		(0.078)	(0.078)	(0.078)	(0.077)
Sec / TA (bank w.a.) - lag t-4		0.076	0.074	0.081	0.058
		(0.051)	(0.051)	(0.051)	(0.050)
IBA / TA (bank w.a.) - lag t-4		0.287***	0.284***	0.285***	0.253***
		(0.049)	(0.048)	(0.049)	(0.048)
Dep / TL (bank w.a.) - lag t-4		-0.175***	-0.157***	-0.153***	-0.132***
		(0.042)	(0.042)	(0.042)	(0.042)
Sec / TL (bank w.a.) - lag t-4		-0.198***	-0.195***	-0.196***	-0.174***
		(0.042)	(0.042)	(0.042)	(0.042)
IBL / TL (bank w.a.) - lag t-4		-0.158***	-0.147***	-0.140***	-0.123***
		(0.038)	(0.038)	(0.038)	(0.038)
Equity / TA (bank w.a.) - lag t-4		-0.224**	-0.228**	-0.205*	-0.154
		(0.107)	(0.106)	(0.106)	(0.104)
Cost eff (bank w.a.) - lag t-4		0.257***	0.270***	0.272***	0.258***
		(0.023)	(0.023)	(0.023)	(0.023)
ROA (bank w.a.) - lag t-4		0.505	1.303**	1.147*	1.136*
		(0.564)	(0.610)	(0.610)	(0.606)
Share NPL (bank w.a.) - lag t-4		-0.176*	-0.171*	-0.151	-0.090
		(0.098)	(0.098)	(0.098)	(0.097)
1_{Q2}			0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)
1_{Q3}			-0.004***	-0.004***	-0.003***
			(0.001)	(0.001)	(0.001)
1_{Q4}			-0.011***	-0.011***	-0.010***
			(0.001)	(0.001)	(0.001)
Var unem (lag t-4)				-0.025***	-0.021***
				(0.004)	(0.004)
Var rstir (lag t-4)				0.001	0.000
				(0.002)	(0.002)
Credit score 3++ (lag t-4)					0.096***
					(0.020)
Credit score 3+ (lag t-4)					0.048***
					(0.010)
Credit score 3 (lag t-4)					0.022***
					(0.006)
Credit score 4+ (lag t-4)					-0.019***
					(0.006)
Credit score 4 (lag t-4)					-0.044***
					(0.005)
Credit score 5+ (lag t-4)					-0.081***
					(0.004)
Credit score 5 (lag t-4)					-0.083***
					(0.005)
Credit score 6 (lag t-4)					-0.108***
					(0.006)
Credit score 7 (lag t-4)					-0.125***
					(0.016)
Credit score 8 (lag t-4)					-0.140***
					(0.018)
Credit score 9 (lag t-4)					-0.157***
					(0.042)
Credit score P (lag t-4)					-0.094***
					(0.010)
Obs. (firm-quarter)	288,425	288,388	288,388	288,388	288,388
Weighted average bank-level control var.	NO	YES	YES	YES	YES
Quarterly dummies	NO	NO	YES	YES	YES
Macroeconomic control var.	NO	NO	NO	YES	YES
Firm-level control var.	NO	NO	NO	NO	YES

Random effect (RE) estimations with robust standard errors clustered at firm level. Regressions based on a firm level quarterly panel. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. All variables in the set of bank-level control variables described in subsection 2.6 are weighted to get a weighted average of these banks' characteristics ("bank w.a.") at firm level. Macroeconomic control variables contain the variations of unemployment rate (Var unem) and or real short-term interest rate (Var rstir). As described in subsection 2.7, firm-level control variables contain credit worthiness dummies, as well as sectoral and geographical dummies (not shown in the table for the sake of brevity). Our third crisis criteria C3 is the opposite of the growth rate of (4-quarter lagged) GDP.

Table 11: Firm level regression results using "C3" crisis criteria

Dependent variable: growth rate of credit at bank level ($\Delta L_{i,t}$)			
Crisis criteria	C1	C2	C3
Intercept (α)	0.053***	0.048***	0.023***
	(0.008)	(0.007)	(0.007)
C_k (α^*)	-0.063***	-0.090***	-0.052***
	(0.012)	(0.020)	(0.011)
SO (α_{SO})	-0.044**	-0.038*	-0.003
	(0.020)	(0.020)	(0.020)
C_k*SO (α^*_{SO})	0.078***	0.098***	0.070***
	(0.016)	(0.027)	(0.015)
COOP (α_{COOP})	0.023**	0.026***	0.037***
	(0.009)	(0.009)	(0.010)
C_k*COOP (α^*_{COOP})	0.036***	0.046**	0.024**
	(0.012)	(0.022)	(0.012)
Size - lag t-4	-0.008***	-0.009***	-0.008***
	(0.002)	(0.002)	(0.002)
Credit / TA - lag t-4	-0.448**	-0.445**	-0.438**
	(0.179)	(0.180)	(0.177)
(Credit / TA)^2 - lag t-4	0.264*	0.264*	0.256*
	(0.143)	(0.144)	(0.141)
Sec / TA - lag t-4	0.021	0.023	0.018
	(0.070)	(0.070)	(0.070)
IBA / TA - lag t-4	-0.125**	-0.122**	-0.129**
	(0.060)	(0.060)	(0.060)
Dep / TL - lag t-4	0.066	0.063	0.069
	(0.060)	(0.059)	(0.060)
Sec / TL - lag t-4	0.052	0.052	0.053
	(0.071)	(0.071)	(0.071)
IBL / TL - lag t-4	0.073	0.070	0.075
	(0.058)	(0.057)	(0.058)
Equity / TA - lag t-4	-0.052	-0.052	-0.048
	(0.077)	(0.077)	(0.077)
Cost eff - lag t-4	-0.107***	-0.105***	-0.108***
	(0.023)	(0.023)	(0.023)
ROA - lag t-4	0.081	0.059	0.083
	(0.530)	(0.533)	(0.534)
Share NPL - lag t-4	-0.471***	-0.480***	-0.469***
	(0.137)	(0.138)	(0.136)
1_{Q2}	0.009**	0.001	0.002
	(0.004)	(0.005)	(0.005)
1_{Q3}	0.002	0.001	0.000
	(0.003)	(0.003)	(0.003)
1_{Q4}	0.003**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
$\Delta L_{i,t-4}$	-0.001	-0.001	-0.000
	(0.013)	(0.013)	(0.013)
Var unem (lag t-4)	-0.001	-0.002	-0.004
	(0.010)	(0.011)	(0.010)
Var rstir (lag t-4)	0.004	0.003	0.006**
	(0.002)	(0.002)	(0.002)
Obs. (bank-quarter)	25,091	25,091	25,091
Bank-specific control var.	YES	YES	YES
Quarterly dummies	YES	YES	YES
Lagged dependent variable	YES	YES	YES
Macroeconomic control var.	YES	YES	YES

Two-stage least squares estimations using $L_{i,t-8}$ to instrument the endogenous lagged dependent variable $\Delta L_{i,t-4}$. Standard errors are robust and clustered at bank level. Regressions based on a bank level quarterly panel. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. The set of bank-level control variables contains all variables described in subsection 2.6, macroeconomic control variables contain the variations of unemployment rate (Var unem) and or real short term interest rate (Var rstir). The three columns respectively show the regression results using our three crisis criteria : C1 is a dummy variable that takes value 1 if the (4-quarter lagged) growth rate of GDP is negative, and 0 otherwise ; C2 is a dummy variable that takes value 1 if the French economy was in recession 4 quarters ago, and 0 otherwise ; C3 is the opposite of the growth rate of (4-quarter lagged) GDP.

Table 12: Bank-level regression results on credit to all types of borrowers

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Appendix 1 - Treatment of bank mergers and acquisitions

As we constructed our dataset, we applied a treatment of bank mergers and acquisitions (M&A). Exploiting an ACPR database that keeps track of these M&A (i.e. which bank merged with or acquired another bank, and when the M&A occurred), we could reconstruct "homogeneous entities" backwards in time, as shown in figure 8. For instance, if the bank entity A acquired bank entity B during 2003Q1, for all subsequent reporting quarters, data provided by bank "entity A" will economically comprise the perimeter of both previous entities before the M&A. Therefore, in order to get a comparable perimeter for quarters before the M&A, we will reconstruct an "homogeneous entity A" by simply adding the figures of the real independent bank entities A and B until 2002Q4. For the sake of simplicity, the "homogeneous entity A" will just be referred to as "entity A", and entity B will never appear on its own in the dataset.

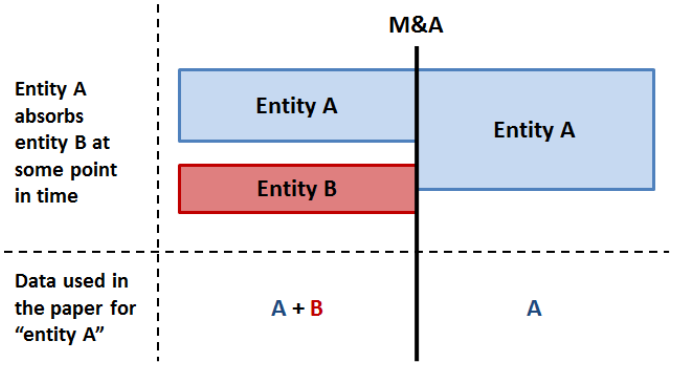

Figure 8: Treatment of data in case of bank M&A

Appendix 2 - List of banks included in the panel and their classification

The table below shows the list of the 276 distinct banks included in the panel and whether they are classified as "private", "cooperative" or "state-owned" banks.

Bank code	Bank denomination	Private	Cooperative	State-owned
10050	STE REUNIONNAISE DE FINT - SOREFI	1	0	0
10128	INTESA SANPAOLO SPA	1	0	0
10218	COOPERATIEVE RABOBANK U.A.	1	0	0
10228	BANQUE LAYDERNIER	1	0	0
10268	BANQUE COURTOIS	1	0	0
10423	THE ROYAL BANK OF SCOTLAND PLC	1	0	0
10468	BANQUE RHONE-ALPES	1	0	0
10550	MERCEDES-BENZ FINANCIAL SERVICES FR SA	1	0	0
10558	BANQUE TARNEAUD	1	0	0
11020	BATI CREDIT	1	0	0
11159	BAIL INVESTISSEMENT FONCIERE	1	0	0
11680	BANQUE DIFFUSION IND NOUVELLE DIN	1	0	0
11688	COFICAPE	1	0	0
11818	GE COMMERCIAL DISTRIBUTION FINANCE S.A.	1	0	0
11938	AGCO FINANCE	1	0	0
11989	BANQUE POUYANNE	1	0	0
12138	CATERPILLAR FINANCE FRANCE S.A.	1	0	0
12158	FIAT FACTORING S.A.	1	0	0
12208	UNICREDIT BANCA DI ROMA SPA	1	0	0
12240	ALLIANZ BANQUE	1	0	0
12280	SOCRAM BANQUE	1	0	0
12328	CIF RHONE ALPES AUVERGNE	1	0	0
12388	CREDIT IMMOBILIER FRANCE FINAN RHONE-AIN	1	0	0
12468	BANQUE CANTONALE DE GENEVE (FRANCE) S.A.	1	0	0
12490	STE FIRE ET CHARBONNIERE SOFICHAR	1	0	0
12569	GE REAL ESTATE FRANCE	1	0	0
12758	DISCOUNT BANK S.A.	1	0	0
12879	BANQUE DELUBAC ET CIE	1	0	0
12978	JCB FINANCE	1	0	0
13088	BNP PARIBAS ANTILLES-GUYANE	1	0	0
13128	COFICA BAIL	1	0	0
13259	BANQUE KOLB	1	0	0
13280	STE FRSE FACTORING INTERNAT FACTO FR SFF	1	0	0
13308	HEWLETT-PACKARD FRANCE FINANCE	1	0	0
13369	ROTHSCHILD MARTIN MAUREL	1	0	0
13400	FCA CAPITAL FRANCE	1	0	0
13489	BANQUE NUGER	1	0	0
13539	BANQUE SOLFEA	1	0	0
13838	CNH INDUSTRIAL CAPITAL EUROPE	1	0	0
13858	LOISIRS FINANCE	1	0	0
13888	HSBC FACTORING (FRANCE)	1	0	0
14118	SYGMA FINANCE S.N.C.	1	0	0
14148	HYPOTHEKENBANK FRANKFURT AG	1	0	0
14218	CLAAS FINANCIAL SERVICES	1	0	0
14228	SGB FINANCE	1	0	0
14270	SELECTIBAIL	1	0	0
14569	UNIBAIL	1	0	0
14579	SOPHIA (2EME DU NOM)	1	0	0
14688	STAR LEASE	1	0	0
14749	PSA BANQUE FRANCE	1	0	0
15078	MFF	1	0	0
15168	GE CORPORATE FINANCE BANK .	1	0	0
15218	BIBBY FACTOR FRANCE	1	0	0
15378	KOMATSU FINANCIAL FRANCE	1	0	0
15498	MAN FINANCIAL SERVICES SAS	1	0	0
15528	LLOYDS BANK PLC	1	0	0
15548	PRIORIS	1	0	0
15648	DEUTSCHE LEASING FRANCE	1	0	0
15728	SEFIA	1	0	0

List of banks included in the panel

Bank code	Bank denomination	Private	Cooperative	State-owned
15940	M.J. BAIL	1	0	0
16000	DIAC	1	0	0
16028	KEY EQUIPMENT FINANCE NORDIC AB	1	0	0
16620	CREDIT DE L EST	1	0	0
16718	C.I.F.D.	1	0	0
16760	FRANFINANCE	1	0	0
16820	AMERICAN EXPRESS CARTE FRANCE	1	0	0
17123	IKB DEUTSCHE INDUSTRIEBANK AG	1	0	0
17340	ACTI-BAIL	1	0	0
17559	STE FIRE SELECTIBAIL	1	0	0
17580	STE FIRE DES PAYS DE L'ADOUR-SEBADOUR	1	0	0
17609	PRIMABAIL	1	0	0
17839	OPEL BANK	1	0	0
17863	DEUTSCHE PFANDBRIEFBANK AG	1	0	0
17959	BANQUE MICHEL INCHAUSPE -BAMI	1	0	0
18020	BNP PARIBAS FACTOR	1	0	0
18029	BNP PARIBAS PERSONAL FINANCE	1	0	0
18069	CIE PR LE DEV DE HOTELLERIE ET TOURISME	1	0	0
18089	BANK AUDI FRANCE	1	0	0
18530	NATIOCREDIMURS STE EN NOM COLLECTIF	1	0	0
18590	BULL FINANCE	1	0	0
18660	COFILOISIRS CIE PR LE FINT DES LOISIRS	1	0	0
18799	HSBC BANK FRANCE S.A.	1	0	0
19020	CREDIT MODERNE ANTILLES GUYANE	1	0	0
19063	LANDESBANK SAAR (SAARLB)	1	0	0
19250	CIE GLE DE LOC D'EQUIPEMENTS C.G.L.	1	0	0
19300	BARCLAYS BAIL	1	0	0
19389	PARICOMI	1	0	0
19399	ANTIN-BAIL	1	0	0
21229	SAPAR FINANCE	1	0	0
21279	STE FIRE DES MIROIRS	1	0	0
21339	FORTIS LEASE	1	0	0
21619	SOPHIA-BAIL	1	0	0
24659	BANQUE CHABRIERES	1	0	0
25819	ILC FRANCE SA	1	0	0
30003	STE GENERALE	1	0	0
30004	BNP PARIBAS	1	0	0
30056	HSBC FRANCE	1	0	0
30076	CREDIT DU NORD	1	0	0
30077	STE MARSEILLAISE DE CREDIT	1	0	0
30478	MONTE PASCHI BANQUE S.A.	1	0	0
30788	BANQUE NEUFLIZE OBC	1	0	0
30958	BNP PARIBAS LEASE GROUP	1	0	0
41040	BANQUE SOFI	1	0	0
41179	AXA BANQUE	1	0	0
41219	BANK OF AMERICA MERRILL LYNCH INT DAC	1	0	0
41249	MUFG BANK, LTD	1	0	0
41629	WESTLB AG	1	0	0
41719	BANQUE PR L INDUSTRIE FRANCAISE B I F	1	0	0
41919	BNP PARIBAS REUNION	1	0	0
41969	BANQUE LEUMI FRANCE S.A.	1	0	0
42789	GE CAPITAL FINANCE	1	0	0
42799	MY MONEY BANK	1	0	0
43649	BANQUE FINAREF	1	0	0
43659	MPB	1	0	0
43759	BANQUE BIPOP	1	0	0
43849	TUNISIAN FOREIGN BANK	1	0	0
43969	UNION IND DE CREDIT U I C	1	0	0
43989	BANCO POPOLARE DI VERONA E NOVARA (FR)	1	0	0
45169	COMPTOIR DES ENTREPRENEURS	1	0	0
45720	FORTIS BANQUE - FORTIS BK SUC FRANCE	1	0	0
60040	STE DE DEV REG DE NORMANDIE	1	0	0
10008	CM-CIC LEASING SOLUTIONS	0	1	0
10057	BANQUE CIC SUD OUEST	0	1	0
10096	LYONNAISE DE BANQUE L.B.	0	1	0
10107	BRED-BANQUE POPULAIRE	0	1	0
10188	BANQUE CHALUS	0	1	0
10206	CRCAM DU NORD EST	0	1	0
10207	BANQUE POPULAIRE RIVES DE PARIS	0	1	0
10278	CAISSE FEDERALE DE CREDIT MUTUEL	0	1	0
10548	BANQUE DE SAVOIE	0	1	0
10607	BANQUE POPULAIRE ANJOU VENDEE	0	1	0
10807	BANQUE POPULAIRE BOURGOGNE FRANCHE-COMTE	0	1	0
10907	BANQUE POP AQUITAINE CENTRE ATLANTIQUE	0	1	0
11006	CRCAM DE CHAMPAGNE-BOURGOGNE	0	1	0
11078	BAIL ACTEA IMMOBILIER	0	1	0
11138	BPCE FACTOR	0	1	0

List of banks included in the panel (continued)

Bank code	Bank denomination	Private	Cooperative	State-owned
11206	CRCAM NORD MIDI-PYRENEES	0	1	0
11306	CRCAM ALPES PROVENCE	0	1	0
11307	CASDEN BANQUE POPULAIRE	0	1	0
11315	CAISSE D'EPARGNE CEPAC	0	1	0
11425	CAISSE D EPARGNE NORMANDIE	0	1	0
11600	CREDIT MUTUEL REAL ESTATE LEASE	0	1	0
11628	LYF	0	1	0
11706	CRCAM CHARENTE-MARITIME DEUX-SEVRES	0	1	0
11830	INTER-COOP	0	1	0
11978	CREDIT MUTUEL FACTORING	0	1	0
12006	CRCAM DE LA CORSE	0	1	0
12128	STE CENTRALE PR FINT IMMOBILIER SOCFIM	0	1	0
12135	CAISSE EPARGNE BOURGOGNE FRANCHE-COMTE	0	1	0
12206	CRCAM DES COTES-D'ARMOR	0	1	0
12406	CRCAM CHARENTE-PERIGORD	0	1	0
12506	CRCAM FRANCHE-COMTE	0	1	0
12549	LOCINDUS S.A.	0	1	0
12579	BANQUE BCP	0	1	0
12749	BPCE BAIL	0	1	0
12870	S I COM I COOP	0	1	0
12906	CRCAM DU FINISTERE	0	1	0
12938	SUD-OUEST BAIL	0	1	0
12939	BANQUE DUPUY DE PARSEVAL	0	1	0
13018	BATIROC BRETAGNE - PAYS DE LOIRE	0	1	0
13070	CREDIT MUTUEL LEASING	0	1	0
13106	CRCAM TOULOUSE 31	0	1	0
13135	CAISSE D EPARGNE DE MIDI-PYRENEES	0	1	0
13149	BANQUE EDEL SNC	0	1	0
13220	STE COOP RENOVATION EQUIP DU COM SOCOREC	0	1	0
13298	BANQUE COM DU MARCHE NORD EUROPE-BCMNE	0	1	0
13306	CRCAM D'AQUITAINE	0	1	0
13335	CAISSE EPARG. AQUITAINE POITOU CHARENTES	0	1	0
13379	BANQUE MARZE	0	1	0
13485	CAISSE D EPARGNE DU LANGUEDOC ROUSSILLON	0	1	0
13506	CRCAM DU LANGUEDOC	0	1	0
13507	BANQUE POPULAIRE DU NORD	0	1	0
13580	FACTOFRANCE	0	1	0
13606	CRCAM D ILLE ET VILAINE	0	1	0
13607	BANQUE POP CENTRE ATLANTIQUE (2E DU NOM)	0	1	0
13698	ESTER FINANCE TITRISATION	0	1	0
13807	BANQUE POPULAIRE GRAND OUEST	0	1	0
13825	CAISSE D EPARGNE RHONE ALPES	0	1	0
13906	CRCAM SUD RHONE-ALPES	0	1	0
14006	CRCAM DE LA GUADELOUPE	0	1	0
14265	CAISSE D EPARGNE LOIRE DROME ARDECHE	0	1	0
14368	CREDIT FONCIER DE FRANCE	0	1	0
14406	CRCAM VAL DE FRANCE	0	1	0
14445	CAISSE D EPARGNE BRETAGNE-PAYS DE LOIRE	0	1	0
14448	CIT FCIER CMUNAL ALSACE LORRAINE-SCF	0	1	0
14505	CAISSE D EPARGNE LOIRE-CENTRE	0	1	0
14506	CRCAM LOIRE HAUTE-LOIRE	0	1	0
14607	BANQUE POPULAIRE MEDITERRANEE	0	1	0
14648	CAPITOLE FINANCE - TOFINSO	0	1	0
14706	CRCAM ATLANTIQUE VENDEE	0	1	0
14707	BQUE POPULAIRE ALSACE LORRAINE CHAMPAGNE	0	1	0
14806	CRCAM CENTRE LOIRE	0	1	0
14907	BANQUE POPULAIRE DU HAUT RHIN	0	1	0
14940	COFIDIS	0	1	0
15135	CAISSE D'EPARGNE GRAND EST EUROPE	0	1	0
15228	SOCIETE FINANCIERE ANTILLES GUYANE	0	1	0
15455	CAISSE D EPARGNE DE LORRAINE	0	1	0
15489	CAISSE FEDER CIT MUT MAIN ANJ BAS NORM	0	1	0
15519	CAISSE FEDER CIT MUT OCEAN	0	1	0
15589	CREDIT MUTUEL ARKEA	0	1	0
15629	CAISSE FEDER CIT MUT NORD EUROPE	0	1	0
15755	CAISSE D EPARGNE DE LORRAINE-NORD	0	1	0
16006	CRCAM DU MORBIHAN	0	1	0
16020	BATIMAP	0	1	0
16106	CRCAM DE LORRAINE	0	1	0
16159	CAISSE FEDER CIT MUT ANTILLES-GUYANE	0	1	0
16190	BPCE LEASE IMMO	0	1	0
16275	CEHDF	0	1	0
16325	CAISSE D EPARGNE D AUVERGNE	0	1	0
16606	CRCAM DE NORMANDIE	0	1	0
16607	BANQUE POPULAIRE DU SUD	0	1	0

List of banks included in the panel (continued)

Bank code	Bank denomination	Private	Cooperative	State-owned
16700	CICOBAIL	0	1	0
16705	CAISSE D EPARGNE D ALSACE	0	1	0
16706	CRCAM NORD DE FRANCE	0	1	0
16707	BANQUE POPULAIRE DE L'OUEST	0	1	0
16806	CRCAM CENTRE FRANCE (3EME DU NOM)	0	1	0
16807	BANQUE POPULAIRE AUVERGNE RHONE ALPES	0	1	0
16839	FINANCO	0	1	0
16850	CAL&F	0	1	0
16906	CRCAM PYRENEES-GASCOGNE	0	1	0
17106	CRCAM SUD-MEDITERRANEE	0	1	0
17149	CRCMM DE BRETAGNE-NORMANDIE	0	1	0
17169	CRC MARIT MUTUEL DU LITTORAL SUD OUEST	0	1	0
17179	CRC MARIT MUT DE LA MEDITERRANEE	0	1	0
17206	CRCAM ALSACE VOSGES	0	1	0
17219	CRC MARIT MUT ATLANTIQUE	0	1	0
17439	STE FIRE PR LE DEV DE LA REUNION	0	1	0
17520	TRANSFACT	0	1	0
17679	STE DE BANQUE ET D'EXPANSION-SBE (2EME)	0	1	0
17806	CRCAM CENTRE-EST	0	1	0
17906	CRCAM DE L'ANJOU ET DU MAINE	0	1	0
17907	BANQUE POPULAIRE VAL DE FRANCE	0	1	0
18025	CAISSE D EPARGNE DE PICARDIE	0	1	0
18106	CRCAM DES SAVOIE	0	1	0
18206	CRCAM DE PARIS ET D ILE DE FRANCE	0	1	0
18306	CRCAM NORMANDIE-SEINE	0	1	0
18315	CAISSE D EPARGNE COTE D AZUR	0	1	0
18507	BANQUE POPULAIRE DE CHAMPAGNE	0	1	0
18706	CRCAM BRIE PICARDIE	0	1	0
18707	BANQUE POPULAIRE VAL DE FRANCE (2EME)	0	1	0
18715	CAISSE D EPARGNE D'AUVERGNE ET LIMOUSIN	0	1	0
18829	ARKEA BANQUE ENTREPRISES INSTITUTIONNELS	0	1	0
18869	BANQUE FRANCAISE MUTUALISTE BFM	0	1	0
18879	BANQUE MONETAIRE ET FINANCIERE B M F	0	1	0
19106	CRCAM PROVENCE - COTE D'AZUR	0	1	0
19169	FINAMUR	0	1	0
19406	CRCAM DE LA TOURAINE ET DU POITOU	0	1	0
19506	CRCAM DU CENTRE OUEST	0	1	0
19519	GEDEX DISTRIBUTION	0	1	0
19706	CRCAM DE L YONNE	0	1	0
19806	CRCAM DE LA MARTINIQUE ET DE LA GUYANE	0	1	0
19906	CRCAM DE LA REUNION	0	1	0
19959	STE FIRE REG PROV ALP C D AZUR SOFIPACA	0	1	0
21570	STE FIRE DE LA N.E.F.	0	1	0
25479	BATIMUR	0	1	0
30002	CREDIT LYONNAIS	0	1	0
30047	BANQUE CIC OUEST	0	1	0
30066	CREDIT INDUSTRIEL ET COMMERCIAL - CIC	0	1	0
30087	BANQUE CIC EST	0	1	0
30258	BANQUE DU BAT ET DES TRAV PUB BTP BANQUE	0	1	0
30948	CIE FIRE DE C.I.C ET DE L'UNION EUROP	0	1	0
40978	BANQUE PALATINE	0	1	0
41539	CA CONSUMER FINANCE	0	1	0
42559	CREDIT COOPERATIF	0	1	0
43199	CREDIT FONCIER DE FRANCE	0	1	0
43799	CA INDOSUEZ WEALTH (FRANCE)	0	1	0
60060	STE DE DEV REG DU NORD ET PAS DE CALAIS	0	1	0
62108	EXPANSO-LA STE POUR LE DEVELOPP REGIONAL	0	1	0
14388	CAISSE FRANCAISE DE FINANCEMENT LOCAL	0	0	1
16160	ALSABAIL ALSACIENNE DE CIT BAIL IMMOB	0	0	1
17290	DEXIA CREDIT LOCAL	0	0	1
17809	ASSURBAIL	0	0	1
18359	BPIFRANCE FINANCEMENT	0	0	1
20041	LA BANQUE POSTALE	0	0	1
44319	BPE	0	0	1
45129	AGENCE FRANCAISE DE DEVELOPPEMENT	0	0	1
Total number of banks: 276, of which:		121	147	8

List of banks included in the panel (continued)

NOT FOR PUBLICATION - Complements or substitutes?

As an alternative approach to the one exposed in this paper, one may explore whether credit granted by the three types of banks (private, state-owned and cooperative) are generally complements or substitutes at the firm level. To do so, we can apply the following specification:

$$\Delta Credit_{PRV,F,t} = \alpha + \beta_1.\Delta Credit_{COOP,F,t} + \beta_2.\Delta Credit_{SO,F,t} + \eta.WABCV_{F,t-4} + \gamma.Q_t + \phi.M_{t-4} + \lambda.FCV_{F,t-4} + \epsilon_{F,t} \quad (4)$$

where $\Delta Credit_{PRV,F,t}$, $\Delta Credit_{COOP,F,t}$ and $\Delta Credit_{SO,F,t}$ denote the mid-point growth rate (MPGR) of credits granted to firm F at time t respectively by private, cooperative and state-owned banks. $WABCV_{F,t-4}$ is the set of lagged weighted-average bank control variables, Q_t the set of quarterly dummies, M_{t-4} the set of lagged macroeconomic variables, $FCV_{F,t-4}$ the set of lagged firm level control variables and $\epsilon_{F,t}$ the error term. With this specification, the two parameters of interest are β_1 and β_2 whose signs will show whether credits granted to a given firm by cooperative and state-owned banks generally positively or negatively commove with credit granted by private banks, in other words whether these types of credit are complements or substitutes at the firm level for multi-bank-type non-financial corporates.

Table 13 displays the results of this specification in five cases: using all time periods, when our crisis criteria C1 equals 1 or 0 and when our crisis criteria C2 equals 1 or 0. We notice that both β_1 and β_2 have positive and significant signs in all regressions, indicating that overall credit granted by the three types of bank are generally rather complements than substitutes at firm level.

Dependent variable: MPGR of credit received from private bank at firm level $\Delta Credit_{PRV,F,t}$					
Specification	All times	C1 = 1	C1 = 0	C2 = 1	C2 = 0
Intercept (α)	-0.593***	-0.459***	-0.569***	-1.236***	-0.589***
	(0.075)	(0.084)	(0.076)	(0.272)	(0.077)
MPGR Coop. Credit (β_1)	0.206***	0.225***	0.203***	0.231***	0.203***
	(0.006)	(0.010)	(0.006)	(0.022)	(0.006)
MPGR SO Credit (β_2)	0.052***	0.057***	0.051***	0.057*	0.050***
	(0.006)	(0.012)	(0.007)	(0.029)	(0.006)
Size (bank w.a.) - lag t-4	0.002	0.011***	0.002	0.041***	0.002
	(0.003)	(0.003)	(0.003)	(0.012)	(0.003)
Credit / TA (bank w.a.) - lag t-4	1.367***	0.628***	1.292***	2.176***	1.361***
	(0.078)	(0.089)	(0.078)	(0.361)	(0.079)
(Credit / TA)^2 (bank w.a.) - lag t-4	-0.690***	-0.230**	-0.659***	-0.794***	-0.696***
	(0.073)	(0.094)	(0.074)	(0.291)	(0.073)
Sec / TA (bank w.a.) - lag t-4	0.461***	0.357***	0.426***	0.392**	0.448***
	(0.048)	(0.063)	(0.049)	(0.179)	(0.049)
IBA / TA (bank w.a.) - lag t-4	0.514***	0.311***	0.478***	0.930***	0.511***
	(0.047)	(0.063)	(0.048)	(0.179)	(0.047)
Dep / TL (bank w.a.) - lag t-4	-0.092***	-0.056	-0.087**	-0.549***	-0.093**
	(0.036)	(0.038)	(0.037)	(0.202)	(0.036)
Sec / TL (bank w.a.) - lag t-4	-0.204***	-0.186***	-0.187***	-0.653***	-0.198***
	(0.039)	(0.043)	(0.040)	(0.176)	(0.040)
IBL / TL (bank w.a.) - lag t-4	-0.142***	-0.071*	-0.126***	-0.684***	-0.133***
	(0.035)	(0.040)	(0.036)	(0.197)	(0.036)
Equity / TA (bank w.a.) - lag t-4	0.576***	0.404***	0.520***	0.728	0.539***
	(0.105)	(0.117)	(0.103)	(0.625)	(0.104)
Cost eff (bank w.a.) - lag t-4	0.042*	-0.037	0.045*	-0.108	0.043*
	(0.023)	(0.030)	(0.023)	(0.126)	(0.024)
ROA (bank w.a.) - lag t-4	-2.884***	-3.366***	-3.101***	-5.837***	-3.111***
	(0.677)	(1.096)	(0.726)	(1.910)	(0.695)
Share NPL (bank w.a.) - lag t-4	-1.232***	-0.705***	-1.192***	-2.419***	-1.249***
	(0.115)	(0.144)	(0.116)	(0.714)	(0.120)
1_{Q2}	-0.002**	0.019*	-0.002*	-0.012	-0.002**
	(0.001)	(0.010)	(0.001)	(0.008)	(0.001)
1_{Q3}	-0.001**	0.015	-0.000	-0.006	-0.001
	(0.001)	(0.011)	(0.001)	(0.007)	(0.001)
1_{Q4}	-0.005***	0.029***	-0.005***		-0.004***
	(0.001)	(0.011)	(0.001)		(0.001)
Var unem (lag t-4)	-0.033***	-0.014	-0.030***		-0.027***
	(0.005)	(0.011)	(0.006)		(0.005)
Var rstir (lag t-4)	0.007***	-0.015***	0.009***	0.005	0.008***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.002)
Credit score 3++ (lag t-4)	0.053***	0.019	0.053***	0.009	0.055***
	(0.018)	(0.030)	(0.020)	(0.057)	(0.019)
Credit score 3+ (lag t-4)	0.042***	0.027*	0.042***	-0.001	0.043***
	(0.010)	(0.014)	(0.011)	(0.028)	(0.011)
Credit score 3 (lag t-4)	0.021***	-0.026***	0.028***	-0.056***	0.024***
	(0.006)	(0.009)	(0.007)	(0.021)	(0.007)
Credit score 4+ (lag t-4)	-0.011	-0.028***	-0.003	-0.040**	-0.007
	(0.006)	(0.009)	(0.007)	(0.018)	(0.007)
Credit score 4 (lag t-4)	-0.020***	-0.016**	-0.016***	-0.045**	-0.018***
	(0.005)	(0.008)	(0.005)	(0.019)	(0.005)
Credit score 5+ (lag t-4)	-0.047***	-0.032***	-0.046***	-0.025*	-0.047***
	(0.004)	(0.006)	(0.004)	(0.015)	(0.004)
Credit score 5 (lag t-4)	-0.046***	-0.032***	-0.046***	-0.050**	-0.045***
	(0.005)	(0.007)	(0.005)	(0.019)	(0.005)
Credit score 6 (lag t-4)	-0.051***	-0.038***	-0.050***	-0.031	-0.049***
	(0.006)	(0.008)	(0.006)	(0.035)	(0.006)
Credit score 7 (lag t-4)	-0.066***	-0.053*	-0.066***	-0.012	-0.066***
	(0.020)	(0.030)	(0.022)	(0.025)	(0.020)
Credit score 8 (lag t-4)	-0.086***	-0.036	-0.084***	-0.052	-0.082***
	(0.020)	(0.028)	(0.022)	(0.063)	(0.021)
Credit score 9 (lag t-4)	-0.120**	-0.014	-0.139**	-0.084	-0.127***
	(0.047)	(0.051)	(0.054)	(0.198)	(0.048)
Credit score P (lag t-4)	-0.042***	-0.007	-0.043***	0.047	-0.041***
	(0.009)	(0.009)	(0.009)	(0.053)	(0.009)
Obs. (firm-quarter)	288,388	47,308	241,80	10,938	277,450

Random effect (RE) estimations with robust standard errors clustered at firm level. Regressions based on a firm level quarterly panel. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are shown in brackets. All variables in the set of bank-level control variables described in subsection 2.6 are weighted to get a weighted average of these banks' characteristics at firm level. Macroeconomic control variables contain the variations of unemployment rate (Var unem) and or real short-term interest rate (Var rstir). As described in subsection 2.7, firm-level control variables contain credit worthiness dummies, as well as sectoral and geographical dummies (not shown in the table for the sake of brevity).

Table 13: Credit by different types of bank: complements or substitutes?