International banking regulation and financial stability : a multidimensional analysis

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Réglementation bancaire internationale et stabilité du système bancaire et financier : une analyse multidimensionnelle

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Réglementation Bancaire Internationale et Stabilité du Système Bancaire et Financier : une Analyse Multidimensionnelle

Résumé

Les conséquences de la crise financière de 2008 ont conduit les différentes autorités de régulation mondiales à se coordonner afin de mettre en place une réglementation bancaire plus uniforme dans le but de stabiliser le système financier dans son ensemble et de prévenir les potentielles futures crises à venir. Toutefois, les amendements mis en place au niveau juridictionnel soulignent la nécessité d'établir une réglementation adaptée et ciblée parallèlement à un cadre général et universel. Nous mettons ainsi en évidence l'importance que ces normes réglementaires s'ajustent aux acteurs économiques, aux instruments économiques ainsi qu'au contexte économique auxquels elles s'appliquent.

Dans un premier temps, nous confirmons la pertinence d'une mesure réglementaire permettant une réduction des exigences de fonds propres associées aux prêts aux petites et moyennes entreprises. Les résultats quant à la cohérence et l'efficacité de ce Facteur de Soutien promeuvent l'instauration d'une réglementation adaptée au risque que présentent les acteurs de l'économie. Deuxièmement, par la mise en évidence des interactions entre la liquidité de financement et la liquidité de marché, intervenant en période de stress uniquement, nous démontrons les bénéfices des exigences élaborées sous une forme contracyclique, que les banques peuvent relâcher et exploiter lorsqu'elles sont confrontées à un choc de liquidité. Enfin, nous révélons l'importance d'une réglementation plus spécifique aux risques que présentent certains outils de financement, tels que les lignes de crédit. Leur concentration, leur volatilité et les limites de leur financement confirment la nécessité d'appliquer une réglementation adaptée à ces instruments aux risques multiples.

Alors que la crise a permis d'uniformiser les exigences réglementaires au niveau mondial, nous présentons les avantages d'une réglementation bancaire plus adaptée, avec des exigences globales harmonisées auxquelles viennent s'ajouter des exigences spécifiques lorsque cela s'avère nécessaire.

Mots Clés : Réglementation bancaire, solvabilité, liquidité de financement, liquidité de marché, financement des entreprises.

International Banking Regulation and Financial Stability: a Multidimensional Analysis

Abstract

The consequences of the 2008 financial crisis led the worldwide regulatory authorities to coordinate their efforts to establish a new global banking regulation with the aim of strengthening the financial system as a whole and preventing potential future crises. However, the amendments put in place at the jurisdictional levels underline the need to establish an appropriate regulation alongside a general framework. In this way, we highlight the importance of regulatory standards adjusting to economic actors, economic instruments and the economic environment.

As a first step, we confirm the relevance of a regulatory measure allowing a reduction in capital requirements associated with lending to small and medium-sized enterprises. The results regarding the consistency and effectiveness of this Supporting Factor promote the introduction of regulation adjusted to the risk generated by economic players. Second, by highlighting interactions between funding liquidity and market liquidity, emerging only during periods of stress, we demonstrate the benefits of requirements developed in a countercyclical form, which banks can release and use when facing with a liquidity shock. Finally, we show the importance of more risk-specific regulation of funding tools, such as credit lines. Their concentration, volatility and funding limits confirm the need for an appropriate regulation of these multi-risk instruments.

While the crisis enabled a standardization of regulatory requirements at the global level, we emphasize the advantages of a more specific banking regulation, with aligned global requirements to which suitable requirements are added when necessary.

Keywords: Banking regulation, capital requirements, funding liquidity, market liquidity, corporate financing.

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Contexte

Les conséquences dévastatrices de la crise financière de 2008 ont conduit les différentes autorités de régulation mondiales à se coordonner afin de mettre en place une réglementation bancaire plus uniforme dans le but de stabiliser le système financier dans son ensemble et de prévenir les potentielles futures crises à venir. Malgré son pouvoir limité en qualité de force exécutoire[1], le Comité de Bâle constitue la plus haute instance d'élaboration des normes bancaires internationales et permet la représentativité de ses 28 juridictions membres. La coopération des autorités de supervision bancaire et des banques centrales a rendu possible l'établissement de normes et standards techniques au niveau international qui ont débouché sur les Accords de "Bâle III" publiés dès 2010 par le Comité de Bâle. Ce nouveau cadre a permis de renforcer et d'harmoniser la règlementation bancaire mondiale au niveau des fonds propres, mais aussi de la liquidité, tout en introduisant une conception macroéconomique des risques, jusqu'alors ciblée sur les risques individuels. Toutefois, tandis que la finalisation de l'application des nouvelles mesures portées par Bâle III est actuellement en cours, les amendements mis en place au niveau juridictionnel soulignent la nécessité d'établir une réglementation adaptée et ciblée parallèlement à un cadre général et universel. La transposition du cadre bâlois au niveau juridictionnel a ainsi révélé l'importance d'uniformiser le cadre réglementaire au niveau mondial, avec des exigences globales harmonisées ainsi que des exigences spécifiques lorsque nécessaires.

Cette volonté de supervision internationale des banques est pourtant bien antérieure à la crise financière de 2008. Avec la création du Comité de Bâle en 1974, les premiers rapports et directives au niveau international apparaissent, qui aboutiront au cadre réglementaire "Bâle I" dès 1988. Principalement basés sur le ratio Cooke, ces premiers accords impliquent une exigence minimale de fonds propres fixée à 8% des actifs pondérés par les risques. Cette

[1] Le Comité de Bâle ne possède pas de pouvoir d'autorité supranationale. Sa crédibilité repose sur la capacité de ses membres à faire adopter ses recommandations par les juridictions nationales compétentes.

réglementation uniquement ciblée sur le risque de crédit souffrira rapidement de l'absence de prise en compte des risques de marché et des risques opérationnels, qui se développent sur la fin des années 1990 avec l'émergence des produits dérivés et structurés.

C'est ainsi qu'en 2004, le Comité de Bâle propose le dispositif révisé "Bâle II". Le ratio Mac Donough couvre désormais le risque de crédit, le risque de marché et le risque opérationnel, tout en conservant un niveau d'exigences de solvabilité à 8%. De plus, le risque de crédit peut s'évaluer selon une approche standard, commune à toutes les institutions, ou selon une approche IRB (*Internal Ratings-Based*) plus spécifiquement élaborée par des modèles internes que les banques auront développés pour estimer les risques supportés. Malgré ces évolutions, ce cadre réglementaire continue à se réformer au fil des crises économiques rencontrées. Notamment, la crise financière de 2008 révèlera de nouvelles déficiences, parmi lesquelles le défaut de supervision du risque de liquidité des banques devra être pallié pour aboutir à une vision plus générale des risques.

Toujours en charge de cette responsabilité, le Comité de Bâle élabore alors Bâle III, un nouveau cadre de réglementation internationale qui introduit des exigences minimales de liquidité permettant de prendre en compte les risques de liquidité auxquels les banques peuvent faire face. D'une part, le *Liquidity Coverage Ratio* (LCR) renforce la solidité des banques à court terme, leur permettant de disposer d'assez de liquidités pour faire face à une crise de liquidité sur 30 jours. D'autre part, le *Net Stable Funding Ratio* (NSFR) assure aux banques une résilience à plus long terme, fondée sur des financements structurellement stables. Un ratio de levier est également adopté afin d'encadrer la taille du bilan des banques et l'effet de levier. Enfin, les exigences de solvabilité sont de nouveau renforcées avec l'amélioration de la qualité et de la quantité des fonds propres. Une nouvelle définition plus stricte des fonds propres est adoptée tandis que le ratio d'exigences minimales passe de 8 à 10,5%. Aussi, ce volet réglementaire aborde la supervision des risques à travers une nouvelle conception, se situant au niveau macroéconomique. Alors que les premiers accords de Bâle considéraient la stabilité financière internationale à travers le seul spectre des risques individuels, les risques systémiques font désormais l'objet d'une attention particulière des autorités de régulation.

Présentation et organisation de la thèse

Le cadre réglementaire international actuel, plus communément appelé "Bâle III", comble ainsi les insuffisances du cadre prudentiel existant avant la crise financière mondiale et favorise un système bancaire plus résilient. Néanmoins, établir des normes réglementaires internationales est une condition indispensable, mais non suffisante, à la stabilité du secteur bancaire. Notre thèse s'inscrit précisément dans ce cadre et **a pour objectif de mettre en évidence qu'il est tout aussi important que ces normes réglementaires s'ajustent aux acteurs économiques, aux instruments économiques ainsi qu'au contexte économique ; chacune de ces dimensions étant spécifique aux juridictions qui transposent Bâle III**. Ainsi, la thèse se décline en trois chapitres, dédiés à chacun de ces éléments. Alors que la crise a permis d'uniformiser les exigences réglementaires au niveau mondial, notre thèse illustre la nécessité de s'orienter vers une réglementation bancaire plus adaptée, avec des exigences globales harmonisées auxquelles viennent s'ajouter des exigences spécifiques lorsque cela s'avère nécessaire.

Le premier chapitre vise à examiner de façon approfondie l'"efficacité" et la "cohérence" d'un nouvel outil réglementaire mis en œuvre spécifiquement pour favoriser l'accès des petites et moyennes entreprises (PME) au crédit bancaire : une réduction ciblée des exigences de fonds propres réglementaires associées aux prêts aux PME. D'une part, l'analyse de l'efficacité de la réforme évalue l'augmentation effective de la distribution de crédit aux PME ; d'autre part, l'analyse de la cohérence de la réforme mesure la légitimité de cet allègement des exigences réglementaires au regard du risque que représentent les crédits aux PME.

Le deuxième chapitre aborde la nécessité de mettre en place une réglementation bancaire flexible et contracyclique, évoluant avec les conditions économiques. L'instauration d'une réglementation sur la liquidité des banques par Bâle III permet de mettre en évidence les bénéfices des exigences élaborées sous une forme contracyclique, que les banques peuvent relâcher et exploiter lorsqu'elles sont confrontées à un choc de liquidité.

Enfin, le troisième chapitre révèle l'importance d'une réglementation plus spécifique aux risques que présentent certains instruments de financement. En effet, la concentration, la volatilité et les limites du financement des lignes de crédit confirment la pertinence de la prise en compte du risque idiosyncratique dans la gestion des lignes de crédit au sein des portefeuilles bancaires et la nécessité d'appliquer une réglementation adaptée à ces instruments aux risques multiples.

Revenons de façon plus détaillée sur chacun de ces trois chapitres, en mettant en avant nos apports et contributions à la littérature existante, mais aussi en dégageant de nos résultats des implications en termes de politique économique.

Efficacité et cohérence d'une réduction des exigences de fonds propres réglementaires associées aux prêts aux PME

Une réglementation homogène appliquée sur des acteurs hétérogènes implique différentes sensibilités quant à ses effets. En particulier, si les petites et moyennes entreprises constituent un moteur essentiel de la croissance en Europe, elles dépendent largement du crédit bancaire pour leur financement externe et sont plus susceptibles de rencontrer des problèmes de financement bancaire que les grandes entreprises. À titre d'illustration, en 2014, les prêts bancaires aux PME étaient encore inférieurs à leur niveau d'avant-crise, contrairement aux grandes entreprises[2]. Or, dans un contexte de renforcement de la réglementation bancaire et d'augmentation des exigences de fonds propres ("EFP" ci-après) des banques, les décisions d'octroi de prêt des banques sont également devenues plus sensibles au cadre réglementaire, comme l'illustrent les récentes contributions à la littérature empirique[3]. Ainsi, en 2014, la transposition des normes de Bâle III dans le droit européen a introduit une réduction de 24% des EFP pour les expositions sur les PME, appelée *facteur de soutien* ("FS" ci-après). Ce nouvel outil réglementaire suppose que toute réduction des EFP devrait permettre de stimuler l'offre de crédit à ces entreprises. Néanmoins, une condition nécessaire pour que le FS soit considéré comme efficace d'un point de vue réglementaire est que les EFP soient cohérentes avec le risque de crédit sous-jacent des PME. Par conséquent, comme le recommandent les législateurs, cette réduction ciblée des EFP doit être régulièrement évaluée selon deux critères : (i) une cohérence des EFP avec le risque de crédit des PME et (ii) un accès au crédit bancaire facilité pour les PME. Ce premier chapitre

[2](EBA, 2016). Report on SMEs and the SME Supporting Factor. Technical report, The European Banking Authority.

[3]Voir par exemple Behn et al. (2016), Bonner and Eijffinger (2016), Jimenez et al. (2017) ou Fraisse et al. (2020) respectivement dans le cas de l'Allemagne, des Pays-Bas, de l'Espagne et de la France.

de notre thèse examine ainsi cette mesure réglementaire en fonction de ces deux dimensions.

La première partie de ce chapitre est dédiée à la cohérence de cette réforme concernant le risque intrinsèque des PME, évaluée par le calcul des EFP *économiques* des banques en utilisant la formule du cadre structurel du risque de crédit de Bâle II/III. Cependant, les EFP réglementaires ne reflètent pas exactement le risque de crédit des PME au sein d'un portefeuille bancaire. En effet, le cadre réglementaire ne considère qu'un seul facteur de risque systématique général, dans lequel la corrélation des actifs, qui mesure la sensibilité des expositions à ce facteur de risque unique, ne varie pas avec la taille des entreprises du portefeuille et dépend principalement de la probabilité de défaut. Par conséquent, la valeur de ce paramètre de risque peut être surestimée, du fait que les PME présentent une probabilité de défaut plus élevée que les grandes entreprises. Afin de pallier ces insuffisances, nous étendons le modèle asymptotique à facteur de risque unique (ASRF) à un cadre multifactoriel qui considère plusieurs facteurs de risque, en fonction de la taille de l'entreprise. Puis nous calculons la contribution marginale de groupes spécifiques d'entreprises, en fonction de leur taille, au total des pertes potentielles sur le portefeuille de prêts bancaires. En comparant les exigences de fonds propres économiques estimées pour des classes de taille spécifiques avec les EFP réglementaires de Bâle II/III pour les mêmes classes de taille, notre approche met en évidence l'hétérogénéité des emprunteurs et permet de vérifier la cohérence des EFP réglementaires avec la contribution de groupes spécifiques d'entreprises au risque de crédit du portefeuille. Plus particulièrement, l'estimation de ces paramètres de risque nous permet également d'évaluer si la différence entre les EFP couvrant les prêts éligibles et les prêts non éligibles est cohérente avec l'allégement de capital induit par le FS.

La seconde partie de ce premier chapitre est consacrée à l'évaluation de l'efficacité de la réforme sur l'offre de crédit aux PME, estimée par la méthode des différence-de-différences. Nous exploitons une condition d'éligibilité au SF pour définir un groupe de traitement composé des expositions éligibles de paires de banque-PME dont l'encours total est inférieur à 1,5 million d'euros et un groupe de contrôle composé des expositions (inéligibles) des autres paires de banque-PME. Nous comparons ensuite l'évolution de l'encours de crédit des expositions éligibles et inéligibles après la réforme (comparativement à avant la réforme). Après avoir estimé l'effet moyen du FS sur l'offre de crédit aux PME éligibles, nous analysons la dynamique de cet effet dans le temps. Dans un troisième temps, nous étudions les sources possibles d'hétérogénéité dans l'effet du FS, selon deux caractéristiques essentielles des entreprises : la taille et le risque des PME. Enfin, nous explorons les éventuelles non-linéarités provenant du seuil d'éligibilité d'1,5 million d'euros d'expositions.

Les résultats relatifs au calcul des EFP économiques sur la base d'un cadre multifactoriel et sa comparaison avec les EFP réglementaires de Bâle III indiquent que les EFP devraient être plus faibles pour les PME que pour les grandes entreprises. D'une part, les plus grandes entreprises sont les plus exposées au risque systématique, donc aux conditions économiques générales, même si leurs taux de défaut sont faibles. D'autre part, les résultats confirment le potentiel de diversification offert par la présence d'expositions sur les PME dans le portefeuille total des prêts bancaires. Alors que les classes de moyennes et grandes entreprises sont fortement corrélées entre elles, les corrélations sont négatives ou très faibles entre les petites et les moyennes/grandes entreprises. Plus spécifiquement, après avoir pris en compte l'incertitude entourant ces estimations et adopté une approche conservatrice, l'amplitude de la réduction des EFP induite par le FS est effectivement cohérente avec la différence d'EFP économiques entre les PME et les grandes entreprises.

En ce qui concerne l'efficacité du FS dans la distribution de prêts bancaires aux PME, nos résultats révèlent que les expositions éligibles ont augmenté de 5 à 10% en moyenne par rapport aux expositions non éligibles après la mise en œuvre du FS (par rapport à avant la réforme), selon les spécifications. Nous constatons également que l'ampleur de l'effet du FS a augmenté avec le temps : l'effet est presque nul la première année après l'entrée en vigueur du FS, mais il s'intensifie ensuite pour atteindre une amplitude de 8 à 10% deux ans après son entrée en vigueur. Concernant l'hétérogénéité de l'impact, l'effet du FS semble beaucoup plus important sur les expositions éligibles des petites entreprises et, plus particulièrement, des micro-entreprises, que sur les expositions éligibles des PME de taille moyenne. De même, les expositions des PME sans notation de crédit bénéficient plus de la mise en œuvre du FS que les expositions des PME considérées comme bien notées ou risquées. Ce dernier résultat souligne que les entreprises sûres ne sont que rarement confrontées à des contraintes de crédit, tandis que les entreprises risquées restent trop risquées du point de vue des banques. Enfin, notre analyse révèle que l'effet du FS est non linéaire. Étant donné que l'encours total de prêts est soumis à la réduction du FS, mais aussi à l'éligibilité du FS, les banques peuvent être incitées à limiter la croissance des expositions qui se situent dans la catégorie du seuil d'éligibilité. En effet, les expositions éligibles classées comme petites ont fortement bénéficié du FS. En revanche, les expositions éligibles moyennes et grandes ont diminué dans la période post-réforme.

Les conclusions de ce chapitre confirment la cohérence et l'efficacité du FS pour les PME. La mise en place de cette mesure réglementaire est légitimée par l'adéquation de l'allègement des exigences réglementaires avec le risque que représentent les crédits aux PME. Par ailleurs, la réforme implémentée spécifiquement pour encourager l'offre de crédit bancaire aux PME a effectivement permis une amélioration de la distribution de prêts aux PME, comblant ainsi une défaillance de la réglementation, trop généralisée, qui pénalisait lourdement et arbitrairement l'accès au crédit des PME. Les résultats mettent néanmoins en lumière un aspect dissuasif et limitant de cette mesure, lié au seuil d'éligibilité des expositions, situé à 1,5 million d'euros, qui conduit les banques à n'accroitre leur offre de crédit aux PME que pour les petites expositions. Après la vérification de la légitimité du FS pour les prêts aux PME et la confirmation que l'ensemble des expositions aux PME présente un risque moindre par rapport aux grandes entreprises, ce seuil d'éligibilité des expositions ne se justifie plus. En ligne avec ces conclusions, les autorités réglementaires ont annoncé une révision de ce seuil d'éligibilité dans le cadre de la mise en place de *Capital Requirements Directive V* par l'Autorité Bancaire Européenne. La mise à jour du cadre réglementaire permet un relèvement du seuil d'éligibilité à 2,5 millions d'euros, au lieu d'1,5 million d'euros, pour l'allègement de 24% des EFP, et ajoute un allègement supplémentaire de 15% des EFP pour toutes les expositions aux PME au-delà de ce nouveau seuil. De cette manière, toutes les expositions aux PME bénéficient d'une réduction des EFP réglementaires en cohérence avec le risque qu'elles présentent. Les PME étant particulièrement affectées par les conditions économiques actuelles liées à la pandémie de COVID-19, les autorités de régulation ont recommandé l'application immédiate et anticipée de ce nouveau cadre révisé du FS aux PME, initialement prévu pour 2021, dans le but de soutenir encore davantage l'offre de prêts aux PME.

Règlementation sur la liquidité des banques

Ce deuxième chapitre analyse une contribution récente de la réglementation bancaire, relative à la liquidité des banques. Les Accords de Bâle III introduisent, pour la première fois, deux ratios de liquidité réglementaires, le *Liquidity Coverage Ratio* (LCR) et le *Net Stable Funding Ratio* (NSFR). Ces ratios poursuivent des objectifs complémentaires, respectivement de promouvoir la résilience à court terme du profil de liquidité des banques et de maintenir un profil de financement stable. Si le second n'est pas encore entré en vigueur, le premier a déjà été mis en œuvre progressivement depuis 2015 et doit permettre aux banques de résister à un choc de liquidité sur 30 jours. Ce chapitre s'inscrit dans ce cadre et vise à examiner la réaction des banques soumises à une liquidité réglementaire lorsqu'elles sont confrontées à un choc de liquidité.

La crise financière mondiale de 2008 a mis en évidence les risques de liquidité des banques, une dimension alors absente de la réglementation internationale. En particulier, les difficultés rencontrées par des banques adéquatement capitalisées ont révélé l'importance de la liquidité bancaire. Les risques de liquidité émergent de différentes composantes et interactions. En effet, lorsque les investisseurs perdent confiance dans la solvabilité des institutions, ils retirent leurs dépôts à court terme et augmentent les appels de marge, empêchant ainsi les banques de respecter leurs engagements financiers. L'augmentation des coûts de financement peut contraindre les banques à procéder à des ventes forcées, ce qui entraine une chute des prix de marché. L'augmentation des coûts de financement, conjuguée à la baisse des prix du marché, entraîne des pertes importantes pour les établissements, ce qui compromet leur solvabilité. Outre l'interaction entre la liquidité et la solvabilité bancaires, l'interaction entre la liquidité de financement[4] et la liquidité de marché[5] a aussi entrainé une remise en question de l'encadrement de la liquidité bancaire.

Pour évaluer la mise en place d'une contrainte de liquidité réglementaire, nous exploitons les données sur un ratio de liquidité réglementaire imposé aux banques françaises depuis 1993, en avance sur Bâle III mais proche du LCR. Deuxièmement, nous mettons en lumière les interactions entre la liquidité de financement des banques et la liquidité de marché. En effet, pendant une crise, les banques peuvent avoir des comportements différents, selon les contraintes réglementaires auxquelles elles sont soumises. Alors que certaines banques voient leur niveau de liquidité s'effondrer, d'autres banques accumulent des liquidités, ce qui leur permet d'assurer un niveau de liquidité conforme. Par ailleurs, nous dépassons le cadre habituel de la littérature retenant généralement une approche par le prix, en considérant l'interaction entre la liquidité de financement et la liquidité du marché par une approche fondée sur la quantité. Enfin, nous considérons également les interactions potentielles entre la liquidité réglementaire et la solvabilité réglementaire des banques, et évaluons la réaction de ces niveaux réglementaires aux chocs de liquidité. Notamment, nous abordons la question de l'utilisation des réserves de liquidités en cas de crise.

Dans la première partie de ce chapitre, nous élaborons un modèle théorique simplifié afin d'illustrer l'impact de la mise en place d'une réglementation relative à la liquidité sur le

[4]La liquidité de financement représente la capacité d'un établissement financier à remplir ses propres obligations financières en levant des fonds à court terme.

[5]La liquidité de marché constitue la capacité à vendre un actif sans subir de variation du prix sur le marché.

comportement des banques. Nous maximisons le profit d'une banque représentative sous des contraintes de solvabilité et de liquidité afin de mettre en évidence ses potentielles décisions de détention de liquidités en interaction avec la liquidité de marché. Précisément, le modèle indique que lorsque la réglementation est contraignante ou que la liquidité de marché est faible, les banques adoptent un comportement de précaution et accumulent des liquidités afin de faire face aux futurs chocs de liquidité : les banques accumulent des titres négociables plutôt que des prêts à risque qui constituent une liquidité peu disponible. En revanche, lorsque les banques bénéficient de niveaux de liquidité plus confortables, de sorte que la réglementation n'est pas contraignante, elles choisissent leur allocation d'actifs plus ou moins liquides en fonction de leur rentabilité, en diversifiant leur portefeuille selon la théorie de Markowitz.

Conformément au modèle théorique, nos estimations empiriques mettent en évidence que les variables reflétant la liquidité de marché n'affectent les ratios réglementaires de liquidité et de solvabilité qu'en période de fortes tensions sur les marchés. En particulier, cet effet négatif est plus important sur la liquidité que sur la solvabilité des banques, ce qui confirme l'existence d'interactions dominantes entre la liquidité de financement des banques et la liquidité de marché pendant les périodes de crise. De manière cohérente, en distinguant l'impact des variables de liquidité de marché sur les différentes composantes du ratio de liquidité réglementaire, nous constatons que l'effet des variables financières se matérialise principalement du côté du passif du coefficient de liquidité, par une augmentation des sorties nettes de liquidités. Par ailleurs, nos résultats confirment l'interaction entre les ratios de liquidité et de solvabilité, indiquant qu'un niveau de solvabilité plus élevé permet d'améliorer le ratio de liquidité.

Étant donné la relation non linéaire entre la liquidité de financement des banques et la liquidité de marché, la mise en œuvre d'une réglementation contracyclique, favorisant l'augmentation de liquidité en période d'expansion et son utilisation en période de crise, à l'instar de la réglementation sur les coussins de fonds propres, parait plus adéquate pour prévenir de futures crises. En l'occurrence, le ratio LCR tel qu'élaboré par Bâle III prend effectivement cette forme contracyclique requise et permet de descendre sous les seuils réglementaires en cas de stress économique pour permettre aux banques d'utiliser les réserves disponibles sans sanction de la part des autorités de supervision. La crise actuelle liée au COVID-19 a rapidement conduit les autorités de supervision à rappeler le caractère contracyclique du ratio LCR par des communiqués de presse dès le mois de mars 2020 et encourager l'usage de la flexibilité déjà intégrée dans la réglementation existante. De concert, la BCE[6] et l'ABE[7] mentionnent l'autorisation des banques européennes à déroger temporairement au seuil réglementaire du ratio LCR de 100% en cette période de tensions économiques et invitent les banques à exploiter leurs réserves de liquidités pour faire face aux difficultés économiques et poursuivre la distribution de crédit aux entreprises. En l'absence d'une telle réglementation évoluant selon le contexte économique, les banques contraintes par ce seuil réglementaire pourraient ne pas être en mesure de respecter leurs engagements, en raison d'une disponibilité de liquidités insuffisante au-delà de ce seuil. Aujourd'hui, le ratio LCR est devenu une mesure de référence du niveau de liquidité des banques, si bien que son utilisation envoie le signal négatif d'un recours à une liquidité de secours, synonyme d'une difficulté qui sera sanctionnée par les agences de notation, sinon par les marchés. Il est donc primordial d'ancrer cet outil réglementaire relatif à la liquidité des banques comme un coussin de liquidité dont le seul dessein est de mettre des liquidités à la disposition des banques en cas de crise, plutôt qu'un indicateur de santé financière.

Un instrument de financement particulier : les lignes de crédit

Le dernier chapitre de cette thèse traite de la nécessité d'adapter la réglementation bancaire également aux instruments économiques à disposition des acteurs. Nous focalisons notre étude sur un instrument qui mérite une attention particulière d'un point de vue réglementaire, les lignes de crédit. Alors que le risque de liquidité des banques lié aux lignes de crédit est généralement perçu comme une possibilité de *run*, à l'image des *runs* sur les dépôts bancaires qui peuvent survenir en période d'incertitude, ce chapitre révèle les multiples risques produits par cet instrument de liquidité. Une ligne de crédit est un accord entre une banque et une entreprise, permettant à cette dernière de tirer des fonds à tout moment, jusqu'à une limite pré-déterminée, à un taux pré-déterminé et pour une période de temps pré-déterminée. En conséquence, d'une part, les banques s'engagent à fournir ces fonds aux entreprises qui rencontrent un besoin de liquidités. D'autre part, les banques financent ces lignes de crédit par les sources de liquidités provenant d'entreprises qui ne tirent pas sur leurs lignes de crédit en même temps. Pour autant que les banques puissent se conformer aux tirages sur les lignes de crédit, cette gestion des liquidités permet une répartition efficace entre les différents utilisateurs à l'échelle de l'économie. Toutefois, lorsque les conditions se détériorent et que les entreprises rencontrent des problèmes de liquidité ou

[6] Lien vers le communiqué de presse de la BCE.
[7] Lien vers le communiqué de presse de l'ABE.

perdent confiance dans la disponibilité des liquidités à l'avenir, elles peuvent tirer sur leurs lignes de crédit simultanément. Dans ce cas, cette allocation efficace de la liquidité ne tient plus et peut mettre en péril le niveau de liquidité des banques.

Au demeurant, ce dernier chapitre révèle que ce problème de liquidité auquel les banques sont confrontées est susceptible d'émerger à tout instant du cycle économique, y compris en période d'expansion. En effet, les lignes de crédit, et plus problématiquement les tirages, présentent les caractéristiques spécifiques suivantes, mettant en danger la gestion des liquidités des banques. Tout d'abord, nous vérifions l'incapacité des banques à remplir leurs engagements de prêt avec leurs remboursements, illustrée par une très faible corrélation entre ces deux composantes. Dans le cas d'un stress de liquidité sur l'ensemble du secteur des entreprises, les banques ne seront pas en mesure de fournir des liquidités à ce secteur parce que le total des facilités de crédit engagées dépassera largement les fonds disponibles provenant des entreprises saines restantes. Deuxièmement, nous mettons en évidence la forte concentration des lignes de crédit et des tirages, qui empêche les banques d'exploiter la diversification de leur portefeuille pour faire face aux tirages. Troisièmement, nous montrons que cette concentration génère une forte volatilité dans les tirages, provenant d'un nombre limité d'entreprises. Dans ce contexte, les banques pourraient donc connaître elles-mêmes d'importants problèmes de liquidité. Par conséquent, nous affirmons qu'il est nécessaire de repenser la question habituelle concernant les lignes de crédit, non plus comme un comportement massif qui pourrait mettre en danger les positions de liquidité des banques en période d'incertitude, mais comme un risque plus concentré pouvant émerger d'une ou quelques entreprises en difficulté dont il faut prendre en compte la capacité de dommages. Les caractéristiques concentrées, volatiles et non-financées des engagements de prêts impliquent que les banques peuvent tomber dans un piège à liquidité à tout moment du cycle économique.

Cette étude est la première, à notre connaissance, qui signale le risque idiosyncratique lié aux tirages des lignes de crédit, dont la mise en péril des positions de liquidité des banques peut se produire à toute phase du cycle, par un petit nombre d'acteurs. Ses résultats confirment la pertinence du risque idiosyncratique dans la gestion des lignes de crédit au sein des portefeuilles bancaires et la nécessité d'appliquer une réglementation adaptée à ces instruments aux risques multiples. En l'occurrence, la réglementation au niveau européen considère un facteur de conversion de capital, qui permet d'appliquer une pondération associée au risque, dans le but d'accumuler des provisions pour ces engagements de facilités de crédit. Or, les fonds propres doivent dépendre du risque associé aux actifs des banques.

Plus les actifs sont risqués, plus la banque doit provisionner de fonds propres. Néanmoins, le facteur de conversion de capital correspond à une pondération limitée, qui ne prend que partiellement en compte le niveau des engagements de prêt. Etant donné les multiples risques induits par les lignes de crédit, il est nécessaire d'évaluer leurs implications régulièrement et d'ajuster la réglementation à ces potentiels préjudices.

Le contexte actuel de la crise économique liée à la pandémie de COVID-19 illustre l'utilisation des lignes de crédit en cas de détérioration de la situation financière des entreprises et l'importance de provisionner ces tirages. Les mesures de confinement (de l'éloignement social à l'isolement) à grande échelle prises par les gouvernements ont des conséquences immédiates sur l'économie réelle et les entreprises, paralysées, qui affrontent un double choc d'offre et de demande. Les conditions de distribution du crédit se sont resserrées et les entreprises réagissent naturellement en exerçant leur droit de tirage sur leurs lignes de crédit pour affronter la crise économique. De manière plus problématique encore, les tirages des lignes de crédit matérialisent de nouveaux prêts au sein des bilans bancaires et requièrent des exigences en fonds propres désormais supérieures. Le facteur de conversion de capital appliqué aux pondérations des risques des lignes de crédit n'étant que partiel, toute transformation de ligne de crédit en prêt réel implique une levée de fonds propres supplémentaires nécessaires pour rester conforme aux exigences de réglementation en matière de capital, au moment le plus inopportun. L'inadéquation d'une réglementation relative aux lignes de crédit et l'insuffisance des provisions requises pour faire face aux pertes potentielles liées aux lignes de crédit octroyées à certaines entreprises en difficulté peut effectivement, à terme, mettre en péril la liquidité des banques.

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Chapter 1

Lower bank capital requirements as a policy tool to support credit to SMEs: evidence from a policy experiment

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Starting in 2014 with the implementation of the European Commission Capital Requirement Directive, banks operating in the Euro area were benefiting from a 24% reduction (the Supporting Factor or "SF" hereafter) in their own funds requirements against Small and Medium-sized enterprises ("SMEs" hereafter) loans. We investigate empirically whether this reduction has supported SME financing and to which extent it is consistent with SME credit risk. Economic capital computations based on multifactor models do confirm that capital requirements should be lower for SMEs. As for the impact on credit distribution, our difference-in-differences specification enables us to find a positive and significant impact of the SF on the credit supply. Nevertheless, results emphasize some drawbacks in the framework of the reform and the reluctance of banks to grant credit to firms close to the eligibility threshold.

* * *

This Chapter is an adaptation of a collaboration with Michel Dietsch, Henri Fraisse and Mathias Lé, which has been published in EconomiX working paper series (EconomiX WP 2019-12). Although we all worked on each part of the paper, most of my contribution focused on the analysis of the effectiveness of the Supporting Factor.

1.1 Introduction

Small and Medium-sized Enterprises ("SMEs" hereafter) finance is a growing concern in Europe. While SMEs are a crucial engine for growth in Europe, they are largely dependent on bank credit regarding their external financing and are much more likely to report issues with bank financing than large corporates. As an illustration, in 2014, bank lending to SMEs was still below its pre-crisis level, in contrast with large corporates (EBA, 2016). To improve SMEs' access to credit in time of crisis, policymakers and central bankers traditionally rely on monetary and targeted fiscal policies.[1] However, in a context of changing bank regulation and rising bank capital requirements ("CRs" hereafter), bank lending decision has also become increasingly more sensitive to the regulatory framework, as illustrated by recent contributions to the empirical literature.[2] Against this background, this chapter investigates the *effectiveness* and the *consistency* of a new regulatory tool implemented specifically to promote SMEs' access to bank credit: a targeted reduction in bank CRs associated with SMEs loans.

In 2014, the transposition of the Basel III standards into EU law introduced a 24% reduction in CRs for exposures to SMEs –labelled *Supporting Factor* ("SF" hereafter)– with the aim of fostering the provision of credit to SMEs. The idea behind this proposal is that any reduction of regulatory capital requirements (CRs) should boost credit availability for businesses. The European legislators have required credit institutions to use this CRs relief for the "*exclusive purpose of providing an adequate flow of credit to SMEs established in the Union*".[3] But, a necessary condition for the Supporting Factor to be effective is that regulatory capital requirements should be consistent with the underlying SME credit risk.

[1] During the financial crisis, targeted monetary policy instruments such as the TLTRO or the ACC have been implemented in Europe. In France, SMEs benefit from specific fiscal deductions related to their investment plan.

[2] See for instance Behn et al. (2016), Bonner and Eijffinger (2016), Jimenez et al. (2017), or Fraisse et al. (2020), respectively in the case of Germany, the Netherlands, Spain and France.

[3] See paragraph 44 of the Capital Requirement Directive (CRDIV) published in the Official Journal of the European Union the 27 June 2013.

Hence, as required by the legislators themselves, this targeted reduction in CRs needs to be regularly evaluated according to two criteria: (i) an easier access to bank credit for SMEs and (ii) the consistency of capital requirements with SME credit risk.

In this chapter, we assess this policy experiment along with these two dimensions. For this purpose, we exploit the French credit register. This dataset is maintained by the Banque de France and offers an almost comprehensive sample of loans granted to corporate businesses operating in France over the last two decades. Importantly, in this dataset, we also observe the credit rating granted by the Banque de France to a large sub-sample of firms, which enables the computation of historical time series of default rates. Based on this dataset, the consistency of the reform regarding the intrinsic riskiness of SMEs is gauged through the computation of banks' *economic* capital requirements using the structural credit risk framework underlying the computation of the regulatory capital requirements. Then, the impact of the reform on the credit supply to targeted SMEs is estimated through the difference-in-differences methodology.

To assess the consistency issue (we refer to this part as the *risk analysis* hereafter), we use the credit risk structural approach, as devoted by Merton (1974). This approach underlies the Basel II/III regulatory capital requirements formula (Gordy, 2003). However, the regulatory capital requirements do not necessarily reflect SMEs credit risk in a bank portfolio. The reason is that, in the regulatory framework, the asset correlation, which measures the sensitivity of exposures to the single risk factor, is invariant with the characteristics of the real portfolios and is assumed to depend mainly on the probability of default. Consequently, the value of this risk parameter appears to be overestimated, as shown by numerous academic papers using real portfolios data.[4] The overestimation of SMEs capital charges comes largely from the fact that SMEs show higher probabilities of default than large corporates.

To compute in a consistent way the capital requirements, we expand the asymptotic single risk factor model (ASRF) to a multifactor framework to take into account differences in risk associated with firms' size. We consider several risk factors, depending on the firm's size, and we compute the marginal contribution of specific groups of firms to the total potential losses on bank loans portfolio, depending on their size. This marginal contribution measures the amount of "economic capital" required to cover the losses associated with each size class, economic capital being defined as the estimate of the worst possible decline in the bank's amount of capital at a specified level of confidence (99.9% in Basel formulas) within a chosen time horizon (one year). Thus, in this chapter, we adopt a lender's perspective and address the consistency issue by assessing firms' size as a driver of systematic credit risk in loans

[4] See Dietsch et al. (2016) for a comprehensive overview of the existing empirical studies on the relationship between asset correlations and firm size.

portfolios. Therefore, our multifactor approach with firms' size as a risk factor departs from the Basel II/III framework, which considers only a single general systematic risk factor, and in which the sensitivity of exposures to risk does not vary with the size of the firms.

In fact, firms of different sizes could not be equally sensitive to the general common single risk factor. Moreover, they could be sensitive to risk factors which are specific to their own size class. Ignoring firms' heterogeneity could generate an overestimation of SMEs credit risk if the regulatory correlation is significantly higher than the empirical correlation estimated by using data of banks' real loans portfolios. On the contrary, by comparing estimated economic capital requirements for specific size classes with the Basel II/III regulatory capital requirements for the same size classes, our approach takes into account borrowers' heterogeneity and allows us to verify the consistency of regulatory CRs with the contribution of specific groups of firms to portfolio credit risk. Moreover, the multifactor approach also takes into account the potential correlations of exposures not only within a group of borrowers of the same size but also between groups of borrowers of different sizes to measure economic capital requirements. To summarize, estimating risk parameters by using real data and adopting a multifactor approach also allows us to assess whether the difference in capital requirements covering eligible loans and non-eligible loans is consistent with the capital relief induced by the Supporting Factor.

For being eligible to the Supporting Factor, SMEs must have (i) an annual turnover lower than €50 million and (ii) a total outstanding amount of credit with a given banking group lower than €1.5 million. We take advantage of this setting to estimate the effect of the SF on the provision of credit to targeted SMEs (we refer to this part as the *credit analysis* hereafter) using a difference-in-differences approach. We first restrain the sample to SMEs, identified as the firms with a turnover lower than €50 million. Then, we define a treatment group made of eligible exposures from pairs of bank-firm with a total outstanding amount below €1.5 million and a control group made of (ineligible) exposures from the remaining pairs of bank-firm. We then compare the evolution of the outstanding amount of credit of eligible and ineligible exposures after the reform (vs. before the reform). We deal carefully with possible identification issues by running several robustness checks.

After having estimated the average effect of the SF on the credit supply to eligible firms, we then investigate the dynamics of this effect over time. Did the banks respond immediately to the reform or, on the contrary, has the SF become increasingly effective quarter after quarter ? To that end, we estimate the effect of the SF *within* each quarter, both before and after the reform. In doing so, we not only gather information about the evolution of the effectiveness of the SF over time but we also test a fundamental assumption of the difference-in-differences estimator: the parallel trend assumption. In a third time, we investigate possible sources of heterogeneity in the effect of the SF. We focus on two crucial firms' characteristics: the size and the riskiness of firms. We classified exposures according to the turnover and the Banque de France rating of firms in the pre-reform period (to avoid any endogeneous feedback loops) and we test whether the effect of the SF is the same for the various groups of firms.

Finally, we explore possible non-linearities by estimating the effect of the SF *conditional* on the *ex ante* size of the exposures. For this purpose, we classify exposures into three buckets based on their average outstanding amount computed over the pre-reform period and we estimate an effect of the SF separetely for each of these buckets. As we will show, there are some reasons to think that all exposures have not benefited in the same way from the SF, owing to the design of the SF.

Our main results can be summarized as follows. Regarding the *risk analysis*, the computation of economic CRs based on a multifactor framework and its comparison with Basel III regulatory CRs do confirm that the CRs should be lower for SMEs than for large corporates. We first find that the largest firms are the most exposed to systematic risk, *i.e.* they are the most exposed to general economic conditions even if their default rates are low. Second, the results of the estimation confirm the potential for diversification provided by the presence of exposures on SMEs in the total bank loans portfolio: while the classes of medium-sized and large firms are highly correlated with each other, we find negative or very small correlations across small firms and medium-sized firms, on the one hand, and large firms, on the other hand.

The higher values of the ratio of regulatory CRs to economic CRs for small size classes reflect an overestimation of SMEs risk relative to large corporates in the regulatory frameworks, even after taking into account the SF. Overall, after considering the uncertainty surrounding these estimates and adopting a conservative approach, we find strong evidence that the SF is consistent with the difference in economic CRs between SMEs and large corporates.

Regarding the *credit analysis*, we find evidence showing that the SF has been effective in supporting bank lending to targeted SMEs. First, we show that eligible exposures have increased by 5% to 10% on average as compared to ineligible exposures after the implementation of the SF (vs. before the reform) depending on the specification. In the most conservative estimation including group specific trends, we still find that the SF has boosted eligible exposures by 2%. This average effect is corroborated to various robustness checks. Then, we find that the magnitude of the effect of the SF has increased over time: the effect is almost zero in the first year after the entry into force of the SF but it has then intensified to reach a magnitude of 8% to 10% two years after the entry into force. At the same time, we do confirm that the trends of eligible and ineligible exposures did not diverge in a significant way before the reform. This test is an important validation of our empirical strategy based on the difference-in-differences estimator.

Concerning the possible sources of heterogeneity, we first find that the effect of the SF seems much stronger on eligible exposures of small and, most notably micro enterprises (*i.e.* firms with a pre-reform turnover lower than €7.5 million) than on eligible exposures of medium-sized SMEs.[5] Then, we find convincing evidence showing that exposures of SMEs with no Banque de France credit rating tend to be more affected by the implementation of the SF than exposures of SMEs considered as safe or risky based on their credit rating. This last result tends to indicate that safe firms are only rarely facing credit constraints (and as a result, they do not really benefit from the SF) while risky firms remain too risky from the point of view of banks, even after taking into account the capital relief provided by the SF. Hence, banks tend to target the firms with no credit ratings that have default rates much lower than firms considered as risky but that are more likely to face credit constraints than safe firms. These two results provide interesting insights regarding the effectiveness of the SF.

Finally, our analysis reveals that the effect of the SF is non-linear. Indeed, one might suspect that the impact of the reform could be limited by the loss of the capital relief as soon as the exposure breaches the €1.5 million threshold. Since the SF applies to the total outstanding amount (*i.e.* the existing stock of credit) and not just to the new loans, not only banks can benefit from the SF without extending any additional loans but also, as increasing the outstanding amount of loans makes them closer to the threshold, the risk to pass above the threshold and, as a result, to lose the CRs discount on the total outstanding amount increases. Given that, banks may have incentives to limit the growth of exposures that are "too large", meaning those exposures that are originally in the vinicity of the threshold of eligibility. We test this hypothesis by estimating the effect of the SF separately on small, medium and large exposures. We find that eligible exposures classified as small (*i.e.* exposures with an average outstanding amount of credit over the pre-reform period lower than €500,000, namely those for which an increase is unlikely to lead to overcome the threshold) have strongly benefited from the SF. In contrast, medium and large eligible exposures have decreased (as compared to the ineligible exposures) in the post-reform period.

[5] This decomposition aims to follow the most accurately the traditional decomposition used by both the OECD and the European Commission.

Overall our results suggest that this disincentive feature of the reform is at play in our data.

Our chapter contributes to three strands of the literature. First, our work relates to the literature exploring empirically the relationship between CRs and lending. This relation has been recently reassessed exploiting the strong capital shortfall induced by the financial crisis, the recent changes in regulation and an easier access to granular data that allows us to control for demand and supply shocks. Recent contributions tend to support a negative impact of higher CRs on credit distribution (Aiyar et al. (2014), Behn et al. (2016), Jimenez et al. (2017) or Fraisse et al. (*forthcoming*)). In contrast to these studies that generally consider the impact of tighter CRs, our paper exploits a policy experiment explicitly designed to support credit growth through a targeted *decrease* in CRs. So far, to the best of our knowledge, this is the first study that analyses the consequences of reduced regulatory CRs, which can provide a more comprehensive understanding of this relationship because there are no reason to think that the effect is symmetric. For instance our results might provide guidance to macroprudential authorities, when relaxing macroprudential buffers targeting SME lending.

Our chapter is also related to the literature about the risk assessment of banks credit portfolio. From the seminal work of Merton (1974) having shaped the credit risk structural approach, a lot of progress has been made regarding credit risk assessment. In particular, this approach underlies the Basel II/III regulatory capital requirements formula (Gordy, 2003). However, the latter does not take into account borrowers' heterogeneity and possible concentration effects coming from potentially correlated defaults across borrowers whose financial situation is driven by "sectoral" systematic risk factors. We contribute to the existing literature by explicitly accounting for concentration/diversification effect using a multifactor framework where firm size acts as risk factors, a choice that is motivated by the SF issue.[6]

Lastly, despite its consequences on the regulatory capital of the European banks, the evaluations of the effectiveness of the SF are scarce. To our knowledge, Mayordomo and Rodríguez-Moreno (2018) is the first and unique academic contribution to assess the reform. Our work complements their analysis by considering the French banking sector over a long time period covering the implementation of the reform, exploiting a very granular data set and analysing the effects of the reform both on the credit distribution and on the risk taken by the banks.[7] Overall, our results support largely their findings.

[6]With respect to this strand of literature, our paper has also the benefit to exploit longer time series of default rates of SMEs.

[7]Mayordomo and Rodríguez-Moreno (2018) use data from the *Survey on the Access to finance and Enterprise* conducted by the ECB and the European Commission to assess the effects of the SF on the

Our chapter contributes to these different strands of the literature, providing a new perspective, with both an analytic examination of the consistency of the CRs associated with SME risks and an empirical evaluation of the effective impact of the SF on the credit supply. The remainder of the chapter is organized as follows: Section 1.2 describes the data and provides descriptive statistics. Section 1.3 presents the institutional background and the detailed definition of the SF. Section 1.4 details the methodology used for our empirical analysis. Section 1.5 is devoted to the presentation of our findings, some alternative specifications and related comments. Section 1.6 provides concluding remarks.

1.2 Data

1.2.1 The French credit register

We use the French national credit register maintained by the Banque de France (*"Centrale des risques"*). This register reports all the credits granted by any resident credit institution as well as some specific institutions like the *Sociétés de financement* (which are entitled to make credit but not to receive deposits on demand) or the investment firms providing credit. The population of borrowers/debtors includes any resident and nonresident legal entity (firms, local governments and administrations) as well as any natural person having a professional activity operating nationwide. Firms are defined here as legal units (they are not consolidated under their holding company when they are affiliated with a corporate group) and identified by a unique national identification number (called a "SIREN" number). They include single businesses, corporations, and sole proprietorships engaged in professional activities. A bank has to report its credit exposure to a given firm as soon as the total outstanding exposure on this firm is larger than €25,000. The credit register provides quarterly information regarding the type of credit granted among 12 distinct types of loans belonging to 6 broad categories (see Appendix 1.A).

The credit register also provides detailed information regarding the size and the creditworthiness of borrowing firms when they have a turnover above €0.75 million or a total outstanding amount higher than €380K. Indeed, the Banque de France estimates internally

European banking sector. The authors use as key indicator to gauge the reform efficiency the question in the survey asking SMEs' managers whether they applied for a loan and whether their application was fully or partially rejected. The authors also run an additional experiment focusing on the exposures around the €1.5 million threshold (e.g. between €1 million and €2 million) and around the introduction date of the SF in Spain (from August to December 2013). In addition to differences in methods and data between their approach and ours, it is worth noting that the French and Spanish banking sectors differ significantly both on their structure –the French one being much more concentrated– and on how they fared through the financial crisis –the Spanish one being confronted with the burst of a housing bubble. Those differences also make additional analysis on the SF impact to our opinion worthwile.

its own credit ratings for a large population of resident firms (about 300,000) and in particular for small firms that are generally not under the scope of the private rating agencies. The Banque de France has been recognized as an external credit assessment institution (ECAI) for its company rating activity. This enables credit institutions to rely on this Banque de France rating to calculate their regulatory capital requirements. The Banque de France has also been recognized as an ICAS - In-house Credit Assessment System - under the General Documentation governing the Eurosystem's monetary policy operations. Therefore, ratings are also used for refinancing bank loans in the Eurosystem Credit Assessment Framework (ECAF).

Both the credit and the risk analyses are run using this common dataset but they are subject to slightly different restrictions that we explain in the following subsections.

1.2.2 Risk analysis

Regarding the *risk analysis*, we restrict the sample to firms that have at least one exposure reported in the French credit register (see Appendix 1.B for more details about the reporting requirement of this register). This population constitutes more than 3 million of observations over the period. We restrict the dataset to the years going from 2004 to 2015, *i.e.* 66 quarters, and to firms having a Banque de France rating. The sample is representative of the French businesses population. For instance, the Banque de France indicates that the database containing all accounting information used to assess the creditworthiness of firms (*Centrale de Bilans*, *Fiben*) represents at least 75% of the turnover of the population of French firms.[8]

1.2.3 Credit analysis

Regarding the *credit analysis*, we are no longer limited by the availability of the credit risk rating. We run the analysis over the period 2010-2016, *i.e.* 4 years before the entry into force of the SF (the *pre* period) and 3 years after (the *post* period). For the purpose of identifying eligible exposures, we aggregate them at the firm-banking group-quarter level using an auxiliary dataset allowing us to identify banking groups and their affiliates. As we suspect that the credit effect of the SF might be observed on very small firms, we do not restrict the sample to firms with available information regarding the Banque de France credit rating.

[8] See Banque de France, 2016, *Rapport de l'Observatoire des délais de paiement.*

We limit our dataset to small and medium-sized enterprises (SMEs) and exclude large companies with a turnover higher than €50 million. The aim there is to contrast the most comparable firms, using the eligibility threshold as the main component of our difference-in-differences specification (see 1.4.2). We could have included non-SME firms such that the eligibility criterium would have been two-folded: we could have compared SMEs and non-SMEs with an outstanding amount of loan lower than €1.5 million. We do not proceed in this way because firms with a turnover higher than €50 million are significantly different from SMEs, especially regarding their relation with bank lending (in particular, they have an easier access to a range of substitutes to bank credit). This is why we limit the sample to SMEs and we discriminate across them using the threshold for eligibility to the SF. We provide additional information about the restrictions made to the dataset in Appendix 1.C.

We also limit the sample of firms to *independent firms*. Anecdotical evidence indicates that banks have sometimes many difficulties to identify precisely the scope of consolidation of companies. By limiting the sample to independent firms, we overcome this uncertainty.

As a result, we end up with an extremely large, unbalanced, dataset of more than 18.5 million of observations corresponding to 1,093,817 unique firms over 28 quarters. Overall, this dataset has several advantages. First, it can be considered as quasi-comprehensive given the low reporting threshold. We only miss few loans to very small firms that are economically insignificant at the aggregate level. Second, we have a long time series at a quarterly frequency. It thus covers a sufficient period before and after the implementation of the SF, which enables us to explore the effects of the reform while allowing banks to take time to react and adjust their lending. Third, we have very granular information, even if we do not have a flow information (new credit issuance), but a stock information (outstanding credit amount). This information at the firm-bank-quarter level enables us to distinguish a given firm-bank pair through many dimensions (e.g. time series, cross-section, banking product) that we exploit in this paper.

1.3 Institutional Framework

SMEs are generally considered as a key driving force for job creation and economic growth in Europe. Furthermore, bank credit is a crucial source of finance for SMEs (Beck and Demirguc-Kunt (2006)) and this is why bank lending to SMEs is a salient political issue in Europe.[9] In 2013, the European Commission assessed that the transition from Basel II to Basel III would lead to an increase in CRs from 8% to 10.5% for the average European

[9] "*SMEs are the backbone of the European economy, providing a potential source for jobs and economic growth*", European Commission, Regulation of the European Parliament and of the Council, 2015.

bank. Against this background, the European legislator decided to introduce a deduction in the CRs for exposures to SMEs when transposing the Basel III standards into EU law.[10] This deduction aims at offsetting the expected increase in CRs due to the transition from Basel II to Basel III for SMEs. It reflects the policy willingness and the general concern that SMEs should not suffer from the consequences of financial crises they are not responsible for. Therefore, under certain conditions, CRs associated with SMEs loans will be reduced by 23.81% [11] or subject to a so called *Supporting Factor* of 0.7619.

The regulation comes into force the 1st of January, 2014. The new regulation defines precisely the SMEs targeted by this CRs relief. Banks can alleviate their CRs for credit risk associated with a given exposure by multiplying these CRs by 0.7619 provided that[12] :

– the exposure is included either in the *retail*, *corporate* or *secured by mortgages on immovable property* regulatory portfolio,

– the borrower/debtor is a firm with a turnover below €50 million. (See Appendix 1.D for more details about the definition of SMEs),

– the total amount owed to the institution and parent undertakings and its subsidiaries, including any exposure in default but excluding claims or contingent claims secured on residential property collateral, does not exceed €1.5 million (See Appendix 1.D for more details about the total amount owed to the institution).

Note also that :

– exposures in default shall be included for the purpose of determining the eligibility, but excluded from the application of the SF,

– these precited criteria should be met on an ongoing basis.

Overall, it is expected that the implementation of the SF leads banks to provide relatively more credit to eligible exposures/SMEs than to ineligible exposures/SMEs.[13] Indeed, for

[10] See Article 501 of the Capital Requirements Regulation (CRR).

[11] The magnitude of this discount was calibrated from the anticipated increase in CRs for the average European bank : 1-8%/10.5%

[12] `https://www.eba.europa.eu/regulation-and-policy/single-rulebook/interactive-single-rulebook/-/interactive-single-rulebook/toc/504/article-id/4902;jsessionid=1BB645BAF83F701B15ABF1B26949F02A`

[13] Formally, a firm *per se* is not considered as eligible or ineligible. Only the exposures are deemed as eligible/ineligible. For instance, a given SMEs can be eligible to the SF with a given bank and, at the same time, ineligible with the other banks. For the sake of simplicity, in the present paper, we will nonetheless use indiscriminately the terms *eligible firms* and *eligible exposures*.

each additional euro of credit granted, the relative cost in terms of CRs is 24% lower than before when this additional euro of credit is granted to eligible SMEs as compared to ineligible SMEs or to non-SMEs. At the margin, banks have thus incentives to increase their lending to eligible SMEs as compared to any other firms.

Nevertheless, as soon as 2014-Q1, the alleviation in CRs applies to the total outstanding amount of credit, and not just at the margin *i.e.* on newly granted loans. This means that any banks whose exposures are eligible will immediately benefit from a 24% discount in CRs on their actual stock of eligible exposures, whatever be their response to the reform. Consequently, we cannot exclude that banks also use the relaxation of capital constraints (resulting from the application of the SF to the (actual) outstanding amount of eligible credit) to provide more credit to non-eligible SMEs, to large companies or even to invest in other classes of assets that are far from the objective of improving credit supply to SMEs.

In this case, the ineligible exposures will also increase following the implementation of the Supporting Factor. However, if this is true, this mecanism acts as a downward bias in our estimation of the effect of the Supporting Factor. Said differently, it will make more difficult to find a positive effect of the SF in our setting as it will become clear in the section 1.4.

1.4 Empirical Strategy: methodology

1.4.1 Assessing the risk consistency of the Supporting Factor

To assess the consistency of regulatory CRs —including the SF– with SMEs intrinsic credit risk, we compare regulatory CRs with CRs computed by using a more comprehensive economic approach provided by a multifactor portfolio credit risk model.[14] This model grounds on the structural credit risk approach, as devoted by Merton (1974). In our implementation of this model, firm size acts as a systematic risk factor. Even if the regulatory formulas for corporate exposures introduce some adjustments related to firm size, the regulatory models do only consider a single general risk factor and they do not account for the impact of other systematic risk factors (Gordy, 2003).

It is important to emphasize why the multifactor model can be used as a benchmark to check the consistency of the capital deduction induced by the Supporting Factor on SMEs loans with the SMEs risk. Therefore, in this section, we first explain why the CRs measures derived from a multifactor framework can be used as benchmarks. Then, we provide a short description of the multifactor framework and describe how we apply it for our risk analysis.

[14] See Appendix 1.G for more details about this methodology.

1.4.1.1 The economic capital as benchmark for CR measurement

There is a relationship between *regulatory CRs* and *economic CRs* derived from a multifactor model. The Basel II/III risk weight regulatory formulas were calibrated using the standard *Asymptotic Single Risk Factor* (ASRF) model (Gordy, 2003). In this framework, bank's total CRs are computed by using two parameters which refer to firm's individual risk, the probability of default (PD) and the loss given default (LGD), and a third parameter - the asset correlation R – which measures the sensitivity of borrowers to a common single systematic risk factor. So, regulatory Risk Weighted Assets (RWAs) are consistent measures of credit risk. However, two calibration choices determine potential differences between regulatory and economic CRs, which justifies to compare the two types of measures. Firstly, in the regulatory formulas, asset correlation R is entirely determined by the PD. But, as measures of the sensitivity of loans to a risk factor, they should in fact vary from one portfolio to another one, depending on its composition. In practice, Basel II/III regulation provides banks with the formulas to compute R, instead of leaving them computing this risk parameter using internal information. Consequently, a main difference between regulatory and economic CRs comes from the value of assets' correlations. Secondly, in the ASRF model, there is only one single risk. However, borrowers' financial health is linked to multiple sources of credit risk which are more or less specific to the risk segment to which they belong. Consequently, risk measurement should account for borrowers' heterogeneity.

Accounting for borrowers' heterogeneity obliges to expand the standard single risk factor model and to adopt a multifactor framework. Moreover, a multifactor model allows the detection of potential concentration (diversification) effects coming from the strong (weak) dependence of borrowers to risk factors which are specific to their own risk segment. In case of realization of unfavorable value of one systematic risk factor, the number of defaults will increase and losses will climb to higher levels. In such a case, the contribution to the portfolio's segment which is exposed to this risk factor will raise, inducing an increase in total losses.

More generally, if the sensibility of exposures to the systematic risk factor which is specific to their segment is high, the relative contribution of this segment to the portfolio's total losses will be high, which corresponds to a situation of credit risk concentration in that segment. So, in a portfolio composed of several segments, using a multifactor model allows us to compute the marginal contribution of each segment to total losses and to observe either the impact of this segment on the concentration of losses or, on the contrary, the role the segment plays in the diversification of the portfolio credit risk.

In practice, this marginal contribution can be expressed under the form of a capital ratio by relating economic CRs needed to cover potential unexpected losses produced to this segment (computed at a given percentile - for instance 99.9 percent - of the probability distribution function of losses) to total exposures of the segment. In this way, we can assess portfolio's concentration and diversification in terms of capital ratio as a common metrics, showing how size factors could contribute to increase or decrease the level of CRs relative to the level given by a single risk factor model.

1.4.1.2 A short view of the multifactor model

The multifactor model we use in this paper belongs to the class of structural credit risk models.[15] It is an extended version of the ASRF model. The extension of the ASRF framework consists in introducing risk factors which can be linked to observable characteristics of borrowers and vary across groups of borrowers. As mentioned before, such an extension improves substantially the computation of the dependency structure across exposures in a loans portfolio, by allowing us to account for potential credit risk concentration which is linked to borrowers' heterogeneity. Here, we assume that firm size reflects borrowers' heterogeneity and we expand the ASRF model by considering a latent risk factor for each size class.

To compute economic capital in this framework, we proceed in two steps. First, we compute portfolios' main risk parameters and in particular the dependence structure among exposures measured by the matrix of variance-covariance within each size class and between classes. Then, we use Monte-Carlo simulations to build the probability distribution function of losses, determine the total portfolio potential losses and compute the marginal contribution of each size class to potential losses, which measures the buffer of economic capital required to cover the losses in each size class.

To estimate risk parameters, we use an econometric model that belongs to the class of generalized linear mixed models (GLMMs) that combines fixed and random effects for observable and (latent) unobservable factors. Indeed, as shown by Frey and McNeil (2003) and McNeil and Wendin (2007a), the GLMM model implements in a coherent way the Merton latent factor default modeling approach, in which the default occurs when the value of the firm's assets becomes smaller than the value of its debt, that is, because firm's assets values are difficult to observe, when the value of a latent variable describing the financial situation of the firm - which depends on the realization of a set of risk factors - crosses an unobservable threshold which determines the default. In this framework, the default threshold is considered as the fixed effect of the GLMM. The systematic risk factors

[15] In the Appendix 1.G, we offer a complete and technical presentation of the model.

are supposed to be latent factors and then correspond to the random effects of the GLMM. Here, random effects are linked to the firm size segmentation of the portfolio.

Thus, in this framework, the default rate is modeled as :

$$P(Y_{ti} = 1|\gamma_t) = \Phi(x'_{ti}\mu_r + z_{ti}\gamma_t) \tag{1.1}$$

in which Y_{ti} the default indicator variable of borrower i at time t depends on (i) a fixed effect measured by the borrower's internal rating μ_r, and (ii) random effects γ_t which are related to a set of factors corresponding to the size segmentation of the portfolio. x'_{ti} is a $(1 \times R)$ vector of dummies that defines the rating of borrower i during time period t, while z_{ti} is the design matrix of the random effects. Taking firm's credit rating histories to build time series of rates of default by portfolio segments, we get estimates of portfolio's credit risk parameters in a multi-factor context. The GLMM model provides estimates of default thresholds considered as fixed effects and covariance matrixes of a set of latent random effects corresponding to the set of systematic size factors. The estimation of such parameters allows the computation of economic capital as buffer of losses.

Once the credit risk parameters are estimated, the distribution of losses at the portfolio level is computed by Monte Carlo simulations, with each simulated realization of the systematic risk factors being converted into a conditional default probability at the rating/size segment level and, finally, into conditional expected losses at the portfolio level. Various quantiles based on risk measures such as Value-at-Risk (VaR) can then be retrieved from the simulated distribution of portfolio-wide losses. The computation of the portfolio's value-at-risk (VaR) and marginal risk contributions are made by using a methodology proposed by Tasche (2009), which grounds on an importance sampling based simulation of expected conditional losses. This methodology has the advantage to take into account the impact of borrowers' heterogeneity on economic capital charges and capital allocation.

1.4.2 Identifying the effect of the Supporting Factor on credit supply

1.4.2.1 The difference-in-differences framework

To assess the effectiveness of the Supporting Factor regarding the provision of credit to SMEs, we rely on the *difference-in-differences* framework. In this setting, we compare a treated group composed of all individuals affected by the reform to a control group made of comparable individuals non-affected by the reform. In our case, the sample is made of French

SMEs, *i.e.* firms with a turnover lower than €50 million (see Section 1.2 and Appendix 1.B for more details about the sample selection). The treatment group will then refer to exposures/SMEs eligible to the SF and the control group will refer to exposures/SMEs non-eligible to the SF.

As described in Section 1.3, a pair of bank-firm $\{b, f\}$ (or more precisely an exposure $\{b, f\}$) is considered as being eligible to the SF when the total *eligible* outstanding amount of credit from bank b toward firm f is lower than €1.5 million. More precisely, we carefully dissociate the exposure used to assess the eligibility to the SF, denoted $\tilde{L}_{f,b,t}$, from the exposure that will benefit from the CRs deduction, denoted $L_{f,b,t}$.[16]

Starting from the first quarter of 2014, all exposures $L_{f,b,t}$ eligible to the SF (*i.e.* exposures where $\tilde{L}_{f,b,t}$ <€1.5 million) have immediately benefited from the 23.8% discount in CRs. We denote by $EL_{f,b,t}$ the variable that indicates the eligibility status of bank b when lending to firm f at quarter t:

$$EL_{f,b,t} = \begin{cases} 1 \text{ if } \tilde{L}_{f,b,t} \leq \text{€}1.5 \text{ million} \\ 0 \text{ if } \tilde{L}_{f,b,t} > \text{€}1.5 \text{ million} \end{cases} \tag{1.2}$$

However, under this definition, a pair of bank-firm $\{b, f\}$ may switch from the treated group to the control group (and *vice versa*) from one quarter to another as the amount $\tilde{L}_{f,b,t}$ used to assess the eligibility to the SF fluctuates over time. Hence, we are facing an important composition issue that could affect the stability of our treatment/control groups. To overcome this issue, we decide to keep only exposures $\{b, f\}$ whose eligibility status is stable over the whole period, *i.e.* we keep all exposures from pairs of bank-firm $\{b, f\}$ that are continuously eligible or ineligible to the SF over the entire period. We thus define $\bar{E}L_{f,b}$ as follows :

$$\bar{E}L_{f,b} = \begin{cases} 1 \text{ if } \tilde{E}L_{f,b,t} = 1 \ \forall \ t \\ 0 \text{ if } \tilde{E}L_{f,b,t} = 0 \ \forall \ t \end{cases} \tag{1.3}$$

This restriction is rather conservative and does not threaten our identification strategy. Indeed, the restriction that we impose leads to exclude (i) eligible exposures that would become at some point ineligible and (ii) ineligible exposures that would become eligible at some point. In the first case, these are fast-growing "treated" exposures that pass above the €1.5 million threshold at some point. Ignoring them tends to reduce the intensity of the response of the treated exposures to the treatment. In the second case, these are likely to be exposures classified in the control group that tends to decrease significantly over time

[16]See Appendix 1.D for more details about the differences between the two quantities.

until they pass below the threshold. By ignoring them, the control group as a whole has a dynamics more favorable than it would be otherwise. In both case, this restriction creates a downward bias in our identification strategy, *i.e.* it makes more difficult for us to detect an effect of the SF.[17]

We finally denote by $Post_t$ the variable indicating the period where the SF has entered into force:

$$Post_t = \begin{cases} 1 \text{ if } t \geq 2014Q1 \\ 0 \text{ if } t < 2014Q1 \end{cases} \tag{1.4}$$

1.4.2.2 The baseline specification

The goal of the *credit analysis* is to test whether the entry into force of the SF in 2014-Q1 has fostered credit supply of banks to eligible SMEs (as compared to ineligible SMEs). For this purpose, we estimate the following classical difference-in-differences specification :

$$ln(L_{f,b,t}) = \alpha + \beta \cdot \bar{E}L_{f,b} \cdot Post_t + \gamma \cdot \bar{E}L_{f,b} + \theta \cdot Post_t + \mu_{b,t} + \omega_b + \rho_f + \epsilon_{b,f,t} \tag{1.5}$$

where:

- $L_{f,b,t}$ refers to the total outstanding amount of loans granted to the firm f by the bank b at the quarter t
- $\mu_{b,t}$, ω_b, and ρ_f denote respectively bank-time fixed effects, bank fixed effects and firm fixed effects (FEs)

In these regressions, the coefficient of interest is β. It indicates to which extent the credit supply evolves differently for eligible pairs of bank-firm $\{b, f\}$ relative to ineligible pairs of bank-firm $\{b, f\}$ after the implementation of the SF compared with the pre-implementation period. We gradually saturate the regressions with firm, bank and time fixed effects to control for possible confounding factors. In some specifications, we even include bank-time fixed effects to control for bank funding shocks among other things (think to the TLTRO

[17] Alternatively, we could be tempted to classify exposures based on their status in the pre-reform period. However, in doing so, we would have created an upward bias. Indeed, in this case, we could misclassify an exposure as "treated" in post (because it is truly a "treated" exposure in pre) while it is not. Such an exposure would have grown significantly between the two periods. As a result, we would have overestimated the dynamics of the group of treated exposures. The opposite is true for the exposures classified in the control group.

for instance). In all regressions, we systematically control for the Banque de France rating and the size of the firms as well as their industrial sector and their geographic location. We cluster our standard errors at the firm level, *i.e.* we allow for some dependency in the standard errors *within* firms but we consider that these standard errors are i.i.d *across* firms (Abadie et al., 2017).

1.4.2.3 Dynamics over time and firm characteristics

Testing the parallel trends assumption We identify the effect of the SF on the credit supply using a difference-in-differences framework. An important identifying assumption of the difference-in-differences setting is the *parallel trends assumption.* We could test this identifying assumption by running a dynamic version of the baseline specification (1.5). Rather than identifying the effect of the SF on the entire post-reform period (as compared to the pre-reform period), we now estimate the differences in the (log of) outstanding amount of credit between eligible and ineligible pairs of bank-firm $\{b, f\}$ *within each quarter.* The specification writes as follows :

$$\begin{aligned} ln(L_{f,b,t}) = \quad & \alpha + \textstyle\sum_t \beta_t \cdot \bar{EL}_{f,b} \cdot \mathbb{1}_t + \sum_t \gamma_t \cdot \bar{EL}_{f,b} + \sum_t \theta_t \cdot \mathbb{1}_t + \\ & \mu_{b,t} + \omega_b + \rho_f + \epsilon_{b,f,t} \end{aligned} \tag{1.6}$$

where $\mathbb{1}_t$ denotes a dummy taking the value of 1 in quarter t and zero otherwise. The set of coefficients $\{\beta_t\}$ estimates the effect of the SF on the provision of credit within each quarter t. We thus expect to find the $\{\beta_t\}$ to be indistinguishable from zero for any quarter t in the pre-implementation period. In this case, we can conclude that the conditional dynamics of the credit received by eligible and ineligible exposures $\{b, f\}$ are not significantly different in the pre-reform period, *i.e.* our setting satisfies the parallel trends assumption.

By constrast, we expect to find the $\{\beta_t\}$ to be significantly positive for any quarter t in the post-implementation period. Above all, this specification is also very informative regarding the dynamics of the reform : does the magnitude of the effect tend to increase over time or, in constrast does this effect overshoot and then fade out after several quarters?

Heterogeneity and firm characteristics We then investigate to which extent the magnitude of the effect of the SF varies along with firm characteristics. We examine three dimensions: (i) the size of the firm, (ii) the riskiness of the firm and (iii) the size of the exposure. For this purpose, we run slightly modified versions of the specification (1.5).

First, firms are sorted according to their size and their riskiness.[18] We define a firm as :

– $Risky_f$ when its Bank of France rating is below to the notch 4 (this range of ratings corresponds to the *speculative grade* category)

– $Safe_f$ when its Bank of France rating is above or equal to the notch 4 (this range of ratings corresponds to the *investment grade* category)

– $Unknown_f$ when its Bank of France rating is equal to the notch 0 ("*No unfavourable information gathered*")

In Table 1.F.1, we present quasi default rates computed for each Banque de France ratings. For this purpose, we use two definitions of default : (i) when an SME receives the Banque de France rating for which at least one trade bill payment incident has been reported and (ii) a more restrictive definition corresponding to SME subject to insolvency proceedings (recovery or judicial liquidation proceedings). The default rates are computed at a one year horizon. Interestingly, we observe that the default rates increase monotonically and continuously as we downgrade in the rating scale. The rating corresponding to the situation where the Banque de France has "*no unfavourable information*" displays a default rate that stands between the default rates of the investment grade category and the default rates of the speculative grade category. As a result, we could consider this category as less risky than speculative grade but more risky than investment grade.

Then, regarding the size of firms, we define a firm as :

– $Medium_f$ when its turnover is higher than €7.5 million but lower than €50 million

– $Small_f$ when its turnover is higher than €1.5 million but lower than €7.5 million

– $Micro_f$ when its turnover is lower than €1.5 million

Our size variable allows us to consider several thresholds (€0.75 million, €1.5 million, €7.5 million, €15 million ...). We have built our size categories to follow the most closely the traditional decomposition used by both the OECD and the European Commission[19] of the population of SMEs into *micro* (Turnover< €2 million), *small* (turnover in [€2 million; €10 million]) and *medium-sized* enterprises (turnover in [€10 million; €50 million]).

[18] More details about the Bank of France rating scale we use can be found here: https://www.banque-france.fr/sites/default/files/media/2016/12/29/the-banque-de-france-rating-reference-guide.pdf.

[19] See `https://stats.oecd.org/glossary/detail.asp?ID=3123` and `http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_en`.

We define these variables based on the characteristics of firms in the pre-reform period because both size and riskiness of firms can be affected by their indebteness. However, the size and the creditworthiness of firms are likely to vary from one quarter to another. Rather than using the value at a specific quarter in the pre-reform (2013-Q4 for instance), we prefer to take the *mode* of the size and the riskiness, *i.e.* we classify the firm as *small* or *risky* based on the size bucket and the Banque de France rating that are the most frequent in the pre-reform period. By doing so, we nonetheless lose few observations.[20]

Finally, we also classify pairs of bank-firm according to the size of their initial exposure. Indeed, we suspect that the incentives provided by the reform become increasingly mixed and ambiguous as the firm's outstanding amount of credit approaches the threshold of eligibility: to avoid loosing the entire capital relief when breaching the €1.5 million threshold, banks may become more reluctant to provide additional credit to firms with an initial outstanding amount of credit too close from the threshold. To test this hypothesis, we classify pairs of bank-firm $\{b, f\}$ as :

- $Small_{b,f}$ when the average pre-reform total "eligible" outstanding amount of credit is lower than €500,000
- $Medium_{b,f}$ when the average pre-reform total "eligible" outstanding amount of credit is comprised between €500,000 and €1 million
- $Large_{b,f}$ when the average pre-reform total "eligible" outstanding amount of credit is comprised between €1 million and €1.5 million

We favor this *ad hoc* classification over a breakdown by quartiles because the very unbalanced nature of the distribution of initial outstanding amount of credit (*i.e.* there is a disproportionate share of very small exposures, those with an outstanding amount of credit lower than €500,000) would prevent us to analyse accurately the effect of the SF around the threshold.

After that, to test each of these sources of heterogeneity, we run a generic specification where we interact all the terms of the baseline equation (1.5) with the various dummy variables built just before[21]:

$$\begin{aligned} ln(L_{f,b,t}) = \; & \alpha + \textstyle\sum_k \beta_k \cdot \bar{EL}_{f,b} \cdot Post_t \cdot \mathbb{1}_{Type=k} + \sum_k \gamma_k \cdot \bar{EL}_{f,b} \cdot \mathbb{1}_{Type=k} + \\ & \textstyle\sum_k \theta_k \cdot Post_t \cdot \mathbb{1}_{Type=k} + \mu_{b,t} + \omega_b + \rho_f + \epsilon_{b,f,t} \end{aligned} \tag{1.7}$$

[20] In the case where the firm has two values for the mode, we ignore the firm.

[21] For instance, $k \in \{Small; Large\}$.

Overall, these specifications allow us to test whether the magnitude of the effect of the SF is stronger or weaker depending on (i) the size of the firm f, (ii) the riskiness of the firm f, as measured by the Banque de France rating, and (iii) the size of the initial exposure between bank b and firm f.

1.5 Results

1.5.1 The effect of the Supporting Factor on bank risk portfolio

To assess the consistency of regulatory CRs for SMEs, and by this way the effectiveness of the SF, we compare, for each size class, the ratio of CRs measured when using the multifactor model parameters with the ratio of CRs given by the regulatory Basel II/III formulas. The economic CRs are computed by using the multifactor risk model presented above. They measure the marginal contributions of the different firm size classes to the total potential losses on a comprehensive bank business loans portfolio. The multifactor model provides a more comprehensive measure of portfolio credit risk, taking into account borrowers' heterogeneity and possible concentration or diversification effects coming from the interactions between systematic risk factors associated with firm size classes. Thus the comparison between the two types of CRs provides an information about the possible over(under)estimation of effective credit risk by the regulatory formula and the possible compensation provided by the SF.

Recall that, in order to estimate the model, we built a portfolio containing the sum of the business loans held by French banks on each firm registered in the French Credit Register. To compute rate of defaults and other portfolio risk parameters by size classes, we used each firm's history of quarterly ratings (including default) in the ratings system of the Banque de France. To compute CRs, we assume a 45% Loss Given Default (LGD) and a 99.9% quantile of the probability distribution function of losses. These parameter values are those we find in the Basel II/III regulatory framework.[22] All models are estimated using annual default rates. Since we are ultimately concerned with the calibration of CRs, we consider not only the credit risk parameters estimates but also CRs dependent on these estimates. More precisely, we compare in each size class the ratio of CRs measured when using the multifactor model parameters with the ratio of CRs given by the regulatory Basel III formulas.

[22]The 45% are the LGD that were used in the so-called Basel II fondation approach that the banks could use in absence of a validated LGD model but with a validated PD model.

In this section, we first assess the level of sensitivity of firms to systematic risk, depending on their size, and the potential for diversification across size segments in the portfolio. Table 1.1 displays the random effect variances –which measure the exposure to systematic risk– and the correlations of the random effects –the correlations between size systematic risk factors –provided by the GLMM model.[23] More precisely, it shows that the largest firms are the most exposed to systematic risk, *i.e.* are the most exposed to general economic conditions, even if their default rates are low. Additionally, a joint equality test across random effects variances rejects the null hypothesis. Moreover, the random effects across the classes of medium-sized and large firms are highly correlated, with correlations ranging between 95% and 100%. However, correlations across small firms and medium-sized, on the one hand, and large firms, on the other hand, are negative or very small, showing a potential for diversification effects between these size classes. Finally, what appears clearly from the results of the estimation is the potential for diversification provided by the presence of exposures on SMEs in the total bank loans portfolio.

Table 1.1: Random effects variances and correlations

Panel A: Random effects variances (%)					
	Retail		*Corporate*		
Size Class:	$[0.75-1.5]$	$[1.5-5]$	$[5-15]$	$[15-50]$	$[>50]$
Estimates	0.0094	0.0034	0.0163	0.0723	0.225
Standard Errors	0.0101	0.0012	0.0144	0.0360	0.0762

Panel B: Correlation matrix of random effects					
Size Class:	$[0.75-1.5]$	$[1.5-7.5]$	$[7.5-15]$	$[15-50]$	$[>50]$
$[0.75-1.5]$	1				
$[1.5-7.5]$	0.6454	1			
$[7.5-15]$	-0.5802	0.2520	1		
$[15-50]$	-0.7361	0.04326	0.9721	1	1
$[>50]$	-0.7698	-0.04406	0.9519	1	1

This table shows the estimated variances of the random effects and their correlation matrix. All parameters in Table 1.1 are significantly different from 0 with p-values lower than 1%. **Source:** Banque de France, authors' calculations.

[23]The estimation also yields 25 (5x5) default thresholds, not shown here for the sake of simplicity. As expected, these thresholds are ordered, reflecting the increasing likelihood of default for lower ratings, and statistically different from 0.

The computation of economic CRs at the size level allows taking into account all different estimated dimensions of credit risk in a consistent way. Table 1.2 allows to compare the value of the economic CRs with the level of the regulatory CRs, under two regulatory regimes: the standard Basel II/III IRB regime and the CRD IV/CRR regime including the SF impact.[24] Table 1.2 shows an increasing relationship between size and the three distinct CRs, reflecting the growing sensitivity to systematic risk factor (a general factor in the regulatory models, the size risk factor specific to each size class in the economic model) with firm size. Moreover, the level of the two regulatory CRs is far superior to the level of the economic CRs, showing a potential overestimation of CRs by the Basel II/III regulatory formulas or the CRD IV/CRR regulatory formulas with a Supporting Factor. Here, we consider the CRs on large corporates (*i.e.* corporates with a turnover of more than €50 million) as a benchmark, which could be motivated by the fact that the SF introduces a deduction of CRs for SME loans with respect to the lack of deduction of CRs for larger corporates. We compute the ratios of the two regulatory CRs relative to the economic CRs (last two columns of Table 1.2).

The comparison of the values of these ratios between size classes allows us to determine whether the size dependence of the regulatory CRs is consistent with that of the estimated economic CRs. The results confirm that the higher values of the ratios for small size classes reflect an overestimation of SMEs risk relative to large corporates in the two regulatory frameworks. In addition, the results also show the CRs reduction provided by the implementation of the Supporting Factor. The ratio of the regulatory CRs to the economic CRs is lower for the CRD IV/CRR model than for the Basel II/III model. But, despite this

[24]Under the Basel II/ III regime the regulatory CRs (for exposures on corporate) are computed accordingly to the following formula :

$$RW = \left(LGD \cdot N\left[(1-R)^{-0.5} \cdot G(PD) + \left(\frac{R}{(1-R)}\right)^{0.5} \cdot G(0.99)\right] - PD \cdot LGD\right) \cdot (1-1.5 \cdot b)^{-1} \cdot (1+(M-2.5) \cdot b) \cdot 12.5 \cdot 1.06 \tag{1.8}$$

where:

$$R = 0.12 \cdot \frac{(1-e^{(-50 \cdot PD)})}{(1-e^{(-50)})} + 0.24 \cdot \left(1 - \frac{(1-e^{(-50 \cdot PD)})}{(1-e^{(-50)})}\right) - 0.04 \cdot \left(1 - \frac{min(max(5,S),50)-5}{45}\right) \tag{1.9}$$

and

$$b = \left(0.11852 - 0.05487 \cdot ln(PD)\right)^2.$$

RW denotes the risk-weight or the capital requirements, R the correlation, b an adjustment factor, S the total annual sales in millions, PD the probability of default, LGD, the loss given default, M the maturity, $N(x)$ is the cdf of a normal distribution $N(0,1)$ and $G(z)$ is the reciprocal of this cdf. Under the CRD IV/CRR regime, the RW is multiplied by the Supporting Factor for the eligible firms. For a conservative approach, every firm of a size class is given the upper bound of the turnover sales. For instance, firms belonging to the [€7.5M-€15M] class are given a €15 million annual total sale. A similar IRB formula is provided for exposure on "other retail", *i.e.* on firms with exposures lower than €1.5 million.

reduction of the CRs, the ratio of regulatory CRs to the economic CRs still remains largely higher for SMEs than for large corporates. Notice that the last row of Table 1.2 (called "all") shows the diversification benefits provided by the existence of exposures on different size classes within the same portfolio. The row corresponds to the weighted average of the different size classes CRs. It shows that the weighted average value of the economic CRs (3.2%) is far below the value of economic CRs for the large corporate (6.3 %), owing to the presence of SMEs exposures less demanding in CRs in the loans portfolio. This saving in CRs is smaller for the regulatory CRs, the regulatory model failing to account for diversification benefits.

Table 1.2: Annual economic and regulatory capital ratios (CR) by size tranches (%)

Size Class	Economic CRs (1)	Regulatory CRs (2)	Regulatory CRs with SF (3)	Ratio (2)/(1)	Ratio (3)/(1)
$[0.75 - 1.5]$	0.83	6.2	5.2	7.5	6.3
$[1.5 - 7.5]$	1.1	9.8	7.5	8.9	6.8
$[7.5 - 15]$	1.7	9.8	6.7	5.8	3.9
$[15 - 50]$	3.2	9.4	5.4	2.9	1.7
$[> 50]$	6.3	10.2	10.2	1.6	1.6
All	3.2	9.5	7.5	3.0	2.4

This table shows the value of capital ratios when using the multifactor model (economic capital) and the regulatory Basel III model or the regulatory CRD IV/CRR model taking into account the supporting factor (SF). For the regulatory models, we used the *IRB other retail* formula for the computation of assets correlation in the smallest size class [0.75-1.5], and the *IRB corporate* formula (with the corresponding size-turnover-adjustment) for the four last classes of medium and large enterprises.
Source: Banque de France, French national Credit Register and authors' calculations.

There is obviously some model uncertainty in economic CRs measurement. To deal with this issue, we use the values of random effect variance displayed in Table 1.1. We inflate the estimates of the random effect variance of the SME by two standard deviations[25] and we reduce the estimate for the large corporate by two standard deviations.[26] With this new set of random effects, we compute both the economic CRs and the Basel II/III regulatory CRs. We find a regulatory CRs to economic CRs ratio equals to 9.10% for SMEs and of 6.47% for large corporates. In order to have the same economic CRs for SMEs and for large

[25] For illustration : 0.0723+2*0.03602=0.1443 for the [€15M-€50M] size class, 0.0163+2*0.0144=0.0451 for the [€5M-€15M] size class and so on...
[26] (0.225-2*0.07615=0.0727)

corporates as for the regulatory ratio, SMEs should benefit from a 71% discount which is very close to the SF calibration (76%).

In sum, economic CRs computations do confirm that the CRs should be lower for SMEs. According to a multiple factor economic capital framework, the SF should be much higher than 25% in order to be consistent with the difference in economic capital between large and small firms. Nevertheless, taking into account uncertainty surrounding the estimates of the multifactor models and adopting a conservative approach, the SF is consistent with the difference in economic capital between SMEs and large corporates.

1.5.2 The effect of the Supporting Factor on the credit supply

As explained in the econometric framework described in Section 1.4.2, we assess the average effect of the SF on the distribution of credit by banks by relying on the *difference-in-differences* specification (1.5). With this specification, we compare the (log of) total outstanding amount of credit of eligible exposures vs. ineligible exposures in the post-reform period (as compared to the pre-reform period). After analyzing the impact of the SF on the average exposure/firm, we implement the other tests detailed in Section 1.4.2.3 in order to provide a comprehensive overview of the impact of the SF.

1.5.2.1 The average impact of the Supporting Factor on the credit distribution

Table 1.3 presents the results associated with the baseline specification (1.5). The dependent variable is the logarithm of the total outstanding amount of credit between bank b and firm f at time t. As a result, we could interpret the estimated coefficient as a semi-elasticity, *i.e.* the estimated coefficient of interest indicates the change in the initial exposure in percent resulting from being eligible to the SF. Importantly, we only consider the effect of the SF at the *intensive margin*, *i.e.* the effect of the SF on existing and positive bank-firm relationships.

We gradually include a set of fixed effects (FEs) in the regressions. We start with a set of quarter, location, industry and size FEs. The result can be found in column (1). Then, we introduce bank, bank-quarter and firm FEs. The role of the bank-quarter FEs is to control for bank funding shocks among other things. For instance, in the case where (i) some banks face a positive funding shock in the post-reform period and (ii) these banks have credit portfolios biased toward small eligible exposures, we could observe a positive coefficient $\hat{\beta}$ but for reasons unrelated to the SF. The results are shown in columns (2) to (4). In column (5), we even include size-quarter FEs to control for all the shocks specific to a given firm size class as it is a crucial dimension of the SF.

Table 1.3: The effect of the SF on the credit supply

	Logarithm of the total outstanding amount of credit					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible · Post	0.087***	0.095***	0.094***	0.043***	0.067***	0.018**
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.007)
Observations	16,331,261	16,331,261	16,331,261	16,275,264	16,275,264	16,275,264
Adjusted R-squared	0.174	0.178	0.178	0.733	0.733	0.733
Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Size*Time FE	No	No	No	No	Yes	Yes
Group-specific trends	No	No	No	No	No	Yes

This table reports the estimates associated with the difference-in-differences specification (1.5). The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total "eligible" outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable of interest *Eligible* · *Post* is the product of these two latter dummies. All regressions control for size, rating, geographic location and industry classes, as well as year-quarter FE. Column (1) displays results associated with these most basic FEs. Columns (2) to (6) display estimates including gradually bank, bank-time, firm, size-time FE and group-specific trends. Standard errors are clustered at the firm level. Clustered standard errors are reported in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

The point estimate ranges from 0.043 to 0.095 indicating that, when an exposure is considered as eligible to the SF, it receives on average between 4.3% and 9.95%[27] more credit than ineligible exposures in the post-reform period as compared to the pre-reform period.

In the last column, we include linear group-specific time trends. This allows treatment and control groups to follow different trends in a limited but potentially revealing way. With this specification, the effect of the SF is now identified through a *relative deviation* from the group-specific trends. Not suprisingly, the magnitude of the point estimate decreases but remains nonetheless sizable and significant (+1.8%). Importantly, we have enough quarters in the pre-reform period to identify accurately the trends from the period preceeding the reform (Wolfers, 2006). Overall, we found that the average exposure between bank b and

[27]See Kennedy (1981) on how to interpret accurately semi-logarithmic elasticity with a dummy variable.

firm f increases by 2% to 10% more after the introduction of the SF when the exposure is eligible to the SF than when it is not.

Robustness tests In order to ensure the robustness of this finding, we perform additional tests that are presented in the Table 1.4. In the first column, we remove exposures with an average outstanding amount comprised in [€1M–€2M]. Indeed, as the exposure gets closer to the threshold, the incentives for banks are increasingly mixed. At the margin, banks still have incentives to provide more credit to eligible exposures as compared to ineligible exposures. However, the bank has to make sure that the exposure will never pass above the threshold because it will then lose the 24% discount on CRs associated with the total outstanding amount of credit. This will provide strong incentives to limit the growth of exposures as they approach the threshold. This is why we remove exposures higher than €1M and lower than €2M where the incentives for banks to extend credit are mixed.[28] The effect is now identified by comparing exposures below €1M (eligible) with those above €2M (ineligible). We still observe a sizable effect of the SF (+6%).

Then, in column (2), we remove exposures just around the threshold, *i.e.* exposures with an average outstanding amount comprised in [€1.4M–€1.6M]. Indeed, we suspect that the outstanding amount of credit we observe in the credit register and the regulatory definition of exposures may not be perfectly aligned. Alternatively, banks may experience difficulties in identifying the total outstanding amount of a given counterpart at the group level on an ongoing basis. In either case, this could give rise to some misclassification. To avoid this issue, we estimate the effect of the SF after removing exposures around the threshold: the main finding remains unchanged.

In column (3), we address the classical serial correlation issue (Bertrand et al., 2004) by collapsing the dataset into two periods (pre and post). After that, we rerun the baseline specification and still find a positive and significant effect of the SF. In column (4) we drop firms whose size (as reported by the Banque de France) is unknown. These are generally very small firms and ignoring them does not affect the initial findings. In column (5), we remove the two quarters surrounding the entry into force of the SF. This is particularly important in the case where banks tend to anticipate a bit the reform. We continue to observe a significant effect of the SF. Finally, in our last robustness check in column (6), we estimate the effect of the SF on a perfectly balanced sample. Said differently, all pairs of bank-firm $\{b, f\}$ have now a positive exposure all along the period studied (2010Q1-2016Q4). We lose a lot of observations but we now have perfectly stable groups over time.

[28] At the same time, regarding exposures slightly *above* the threshold, banks may have incentives to let the exposures diminish as the loan is amortized in order to benefit from the 24% discount on CRs once the exposure falls below the threshold of eligibility.

This is a way to avoid any composition effect. We observe that the estimated effect of the SF remains unchanged.

Table 1.4: The effect of the SF on the credit supply: robustness checks

	Logarithm of the total outstanding amount of credit					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible * Post	0.059***	0.044***	0.029**	0.036***	0.063***	0.051***
	(0.010)	(0.010)	(0.014)	(0.010)	(0.012)	(0.011)
Observations	16,214,490	16,274,136	1,665,354	8,930,159	13,808,816	5,144,383
Adjusted R2	0.728	0.733	0.583	0.697	0.727	0.787
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	**Avg exp in [0;1000[& [2000-5000[**	**Avg exp in [0;1400[& [1600-5000[**	**Collapse in 2 periods**	**Drop firms with unknown size**	**Drop [2013Q3-2014Q2]**	**Balanced sample**

This table reports the estimates associated with the difference-in-differences specification (1.5) on various subsamples. The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total "eligible" outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable of interest *Eligible* $\cdot$ *Post* is the product of these two latter dummies. In column (1), we run the difference-in-differences estimation on a subsample excluding pairs of bank-firm with an average outstanding amount of credit between €1M and €2M. Column (2) estimates the effect of the SF on a subsample excluding pairs of bank-firm with average outstanding amount of credit between €1.4M and €1.6M. Column (3) reports the coefficient of interest after collapsing the data into 2 time periods (pre and post) to overcome serial correlation issues. Column (4) reports our estimations on a subsample excluding firms whose size (turnover) is unknown. Column (5) reports estimations after dropping the period surrounding the implementation of the SF, *i.e.* from 2013Q3 to 2014Q2. Finally, column (6) shows estimates based on a perfectly balanced sample, *i.e.* we keep all pairs of bank-firm b, f that have a positive exposure over the entire period considered (2010Q1-2016Q4). All regressions control for size, rating, geographic location, industry, bank, bank-time, firm, as well as year-quarter FEs. Standard errors are clustered at the firm level. Clustered standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

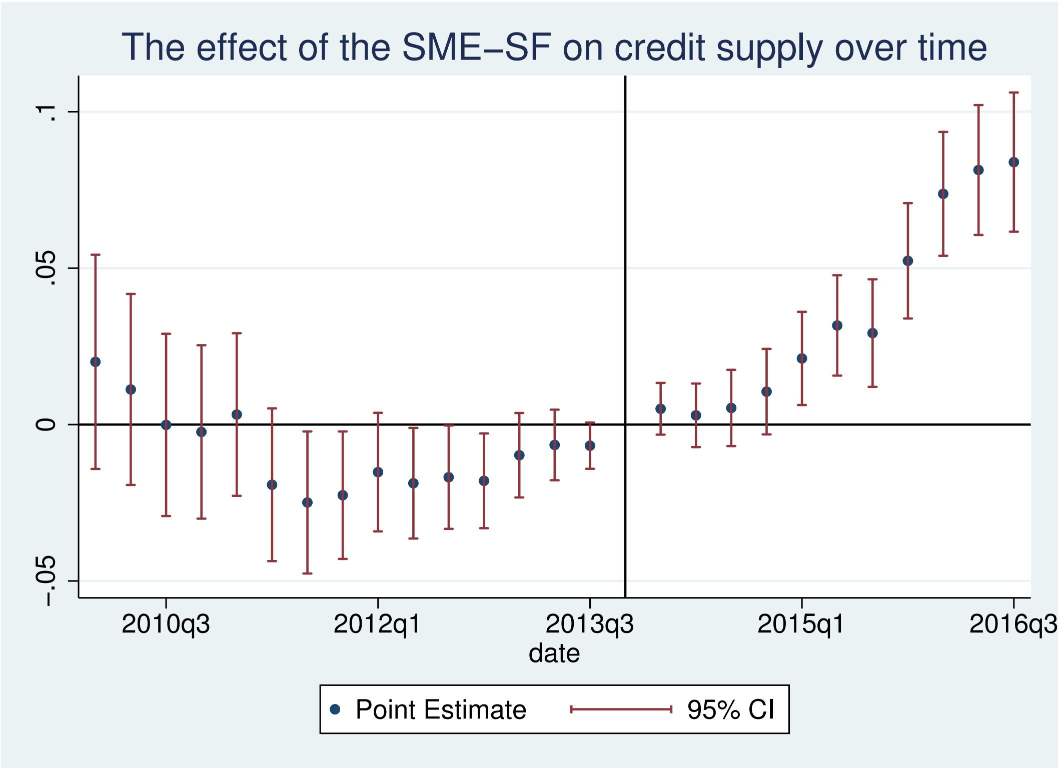
1.5.2.2 Dynamics of the effect over time and the parallel trend assumption

The difference-in-differences estimator hinges on an important assumption: the fact that the treated group and the control group have similar trends in the outcome variable throughout the period preceeding the reform. We can test this assumption by estimating a dynamic version of the baseline specification in which we estimate the effect of the SF *within* each quarter. Above all, this regression is informative regarding the dynamics of the effect over time: have banks responded immediately to the reform or, on the contrary, has the SF become increasingly effective quarter after quarter? Has the effect of the SF on the credit supply persisted over time or has the initial impulse faded out after few quarters (for instance, as a result of the uncertainty surrounding the nature of the reform: temporary or permanent)?

To answer these questions, we run the specification (1.6). Rather than presenting the numerous coefficients in an extended table, we plot the results in the Figure 1.1. In this figure, we represent the coefficients estimated within each quarter as well as the corresponding 95% confidence bands. We define the reference period as 2014Q1 and materialize it with the vertical black line. All the coefficients must be interpreted with respect to this reference period. The underlying regression includes time, location, industry, size, rating, bank, firm and bank-quarter FEs.

First, we do not observe significant differences between the eligible and the ineligible exposures in the period before the reform. Except for few quarters where the difference between the control and the treated group is marginally significant at the 5% level (albeit negative), the figure reveals that the two groups have similar dynamics in the pre-reform period. This is a validation of the common trends assumption. Second, when we look at the post-reform period, we observe that the effect of the SF on the credit supply is not distinguishable from zero for the first four quarters following the entry into force of the SF. However, starting from 2015-Q1, the dynamics of the outstanding amount of credit received by eligible and ineligible groups tends to diverge increasingly and significantly. Said differently, the effect of the SF tends to be stronger over time. In 2016, the magnitude of the effect lies between 5% and 10%, at a much higher level than the baseline estimate.

Figure 1.1: The effect of the SF on the credit supply: dynamics over time



Note: This figure shows the estimates associated to the difference-in-differences specification (1.6). This specification assesses the effect of the SF on credit supply to SMEs quarter after quarter. The blue dots refer to the point estimates associated with the difference in credit distribution between eligible SMEs and ineligible SMEs within each quarter. The red bars indicate the 95% confidence intervals associated with these point estimates. The vertical line indicates the implementation of the SF reform, in January 2014. The underlying econometric specification controls for size, rating, department and industry classes, as well as year-quarter FEs and it includes bank, bank-time and firm FEs.
Source: Banque de France, authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

1.5.2.3 Heterogeneity of the effect of the SF

We now investigate in more details to which extent the effect of the Supporting Factor varies along with firm/exposures characteristics. We focus on three dimensions : the size of firms, their riskiness (as measured by the Banque de France rating) and the size of the exposure. We run the generic specification (1.7) using these three dimensions one by one. The results of these tests are presented in the Tables 1.5 and 1.6.

Firm characteristics In the first column of the Table 1.5, we test whether the SF has the same effect on eligible exposures from medium-sized, small and micro firms. For that purpose, we classify SMEs as medium-sized, small or micro according to their size classes reported in the credit register and based on the turnover of firms. Then, in the second column of the Table 1.5, we test the magnitude of the effect of the SF on the provision of credit by banks depending on the riskiness of SMEs. We classify the SMEs as safe or risky according to their Banque de France rating.

As explained in Section 1.4.2.3, we classify an SME as large or risky according to the most frequent value observed in the pre-reform period. By doing so, we want to avoid endogeneous feedback loops where the response to the SF affects the size or the riskiness of the firm. Indeed, a firm receiving relatively more credit is likely to grow faster or to have an increasing leverage. Both of these mechanisms would affect the size or the riskiness of firms.

The result of this first test in column (1) is unambiguous. While eligible exposures from *medium-sized* enterprises do not grow at all (as compared to ineligible exposures), the eligible exposures from *micro* enterprises grow by 3% (as compared to ineligible exposures) and those from *small* enterprises grow by 13% (as compared to ineligible exposures). The effect of the Supporting Factor is the strongest for enterprises with a turnover higher than €1.5M but lower than €7.5M. In contrast, no effect can be found on the largest SMEs. This finding is not constistent with those of Mayordomo and Rodríguez-Moreno (2018). Using the *Survey on the Access to Finance of Enterprises*, they found that "*the SF alleviates credit rationing for medium-sized firms that are eligible for the application of the SF but not for micro/small firms*". But we have to keep in mind that these findings come from two differents sources and use two distinct methodologies. Furthermore, in their analysis the authors take firm size as a proxy for firm riskiness and conclude that "*this finding is in line with the fact that micro/small firms are riskier than medium firms, and hence, they are not treated equally to medium-sized firms by banks.*". Interestingly, we are able to analyse separately the size and the riskiness of firms thanks to the Banque de France credit rating. As a result, we can push the analysis further.

The result of the second test in column (2) is less clear-cut. We observe that the effect of the SF on exposures from SMEs classified as risky (speculative grade) does not diverge from the effect of the SF on exposures from firms deemed as safe (investment grade): in both cases, the effect is largely insignificant.[29] However, we find that exposures from SMEs for which the Banque de France has "*no unfavourable information gathered*" tend to benefit

[29] We still find no significant differences between risky and safe SMEs when we restrict the sample to firms with a known Banque de France rating.

from the SF.[30] Interestingly, the SMEs with "*no unfavourable information*" –*i.e.* firms with unknown ratings– have a quasi default rate that stands between the quasi default rates of risky and safe SMEs as shown in Table 1.F.1 of Appendix 1.F. Hence, the results of this test indicate that neither the most risky firms nor the safest ones have been targeted by banks when responding to the SF. One possibility to explain this result is that the safest SMEs are largely insensitive to the SF because their are rarely facing credit constraints while riskier SMEs remain too risky from the banks' point of view, even after accounting for the capital relief coming from the SF.

How do these two results interact with each other? Indeed, the vast majority of firms with no Banque de France credit ratings are firms classified as *micro* enterprises. To understand in more depth the relation between size and riskiness, and to understand whether the former can be considered as a good proxy for the latter, we replicate the results from column (2) in terms of riskiness over the various size categories. In columns (3), (4) and (5), we examine how the effect of the SF varies along with Banque de France ratings for the subsamples of respectively *medium-size*, *small* enterprises and *micro* enterprises. The results confirm that these two dimensions do not convey the same information, albeit they are interelated. We observe that for medium-sized firms, no specific pattern can be found: the magnitude of the coefficients tends to support the hypothesis that only firms with unknown credit ratings benefit from the SF, but this result lacks statistical significance to be conclusive. Regarding the sample of small firms, our result indicates that the effect is the strongest for firms considered as safe (investment grade) and, to a lesser extent for firms with no credit ratings information. Finally, among the population of micro firms, only those with no information regarding the Banque de France credit ratings seem to benefit from the SF. These results are consistent given that the micro firms with no credit ratings have default rates that are similar to those of small firms considered as safe (see Table 1.F.1 of Appendix 1.F).

Overall, our results show that the SF primarily benefits to small and micro enterprises and firms with no credit rating. More precisely, the effect is found to be the strongest for small enterprises categorized as safe as well as micro enterprises with no credit rating. Thus, the SF gave banks an extra incentive to grant credit to firms which are not closely monitored and that suffer more from asymmetry of information (*i.e.* firms with no Banque de France credit rating). It clearly shows that the credit distribution to those firms was somewhat constrained by the regulatory weights before the implementation of the SF.

[30] Importantly, as soon as one default on trade bills is reported, the firms will be immediately classified as risky. As a result, this category indicates at least that the firm is not performing too poorly.

Table 1.5: The effect of the SF on the credit supply: breakdown by firm's characteristics

	Logarithm of the total outstanding amount of credit				
	(1)	(2)	(3)	(4)	(5)
Eligible · Post · *Medium-sized*	-0.018				
	(0.056)				
Eligible · Post · *Small*	0.128***				
	(0.016)				
Eligible · Post · *Micro*	0.029**				
	(0.012)				
Eligible · Post · *Risky*		-0.001	-0.085	0.026	-0.019
		(0.015)	(0.075)	(0.017)	(0.027)
Eligible · Post · *Unknown risk*		0.049***	0.234	0.118*	0.051***
		(0.012)	(0.150)	(0.067)	(0.012)
Eligible · Post · *Safe*		0.027	0.009	0.129***	-0.107
		(0.041)	(0.093)	(0.046)	(0.089)
Observations	15,050,896	15,132,625	150,195	1,318,019	13,327,670
Adjusted R-squared	0.723	0.724	0.472	0.541	0.747
Sample	All firms	All firms	Medium-sized	Small	Micro
Bank FE	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Test medium vs small	.01				
Test small vs micro	0				
Test risky vs unknown		.01	.06	.18	.02
Test safe vs unknown		.61	.2	.89	.08

This table reports the estimates associated with the difference-in-differences specification (1.5). The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total eligible outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable *Eligible* · *Post* is the product of these two latter dummies. We interact this last variable with 2 characteristics of the firms: the size as measured by the turnover and the riskiness as assessed by the rating provided by the Banque de France. Firms are classified according to the most frequent value observed in the pre-reform period. We distinguish the riskiness of the firms according to their rating in 3 classes: risky (speculative grade), non-rated and safe (investment grade). Likewise, we distinguish the size of the SME in 3 classes: medium-sized, small and micro enterprises. All regressions control for size, rating, geographic location, industry, bank, bank-time, firm, as well as year-quarter FEs. Standard errors are clustered at the firm level. Clustered standard errors are in brackets.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

Non linearities Our third test is slightly different. Rather than contrasting the effect of the SF with respect to firm characteristics, we now explore how the effect of the SF differs depending on the size of the exposure. Say differently, we test for non linearities in the effect of the SF on the credit supply. The rationale behind such a test comes from the fact that, as explained before in Section 1.5.2.1, as the outstanding amount of credit associated with the pair of bank-firm $\{b, f\}$ approaches the threshold of eligibility, the incentives given to banks by the SF becomes increasingly ambiguous. On the one hand, it is still relatively less costly in terms of CRs to lend to eligible pair of bank-firm at the margin, but on the other hand, the risk to pass above the threshold (and therefore to lose the CRs discount on the *total* outstanding amount of credit) increases at the same time. Consequently, as the exposure gets closer to the threshold, banks may become increasingly reluctant to extend additional credit to the relevant firms.

As a result, we expect that the effect of the SF should become proportionally weaker as the size of the exposure increases. Given that the coefficient of interest β indicates an effect of the SF in relative terms, the coefficient associated with the largest eligible exposures could even become negative, indicating that these exposures have decreased (as compared to ineligible exposures) after the implementation of the SF.

To implement this test, we classify exposures according to their average outstanding amount computed over the pre-reform period as explained in Section 1.4.2.3. We define three buckets: *small* ([0-€500,000]), *medium* ([€500,000-€1M]) and *large* ([€1M-€1.5M]). Then, we estimate simultaneously a coefficient β for each of these three buckets using the generic specification (1.7). This test is in line with the identification strategy implemented by Mayordomo and Rodríguez-Moreno (2018). However, we favor a *discrete* functional form while they use a *continuous* functional form.

The results of this test are displayed in Table 1.6. We report several specifications including various fixed effects. We observe that the coefficient associated with exposures categorized as *small* is systematically positive and significant while the coefficient associated with the two other buckets of exposures (*medium* and *large*) are significantly negative: as compared to the ineligible exposures, the eligible exposures considered as *small* tend to grow more after the entry into force of the reform (between +9% and +15%) while this is not the case for *medium* and *large* eligible exposures. We even observe that the *medium* and *large* exposures tend to decrease in the post-reform period.

These results confirm that banks have primarily supported exposures of small size as a result of the implementation of the Supporting Factor. This finding can be rationalized if we consider that the design of the SF provides ambiguous incentives. This ambiguity comes from the fact that the SF does not target flows of new credit but rather provides a CRs relief on the existing stock of credit. As a result banks may benefit from the SF without any action being required on their part. Around the threshold of eligibility, banks may even have incentives to curb credit growth in order to avoid passing the threshold and losing the CRs relief on the total outstanding amount of credit. This last hypothesis is consistent with our results: the exposures classified as *medium* or *large* tend to decrease (in relative terms) after the entry into force of the SF. To the best of our knowledge, we are the first to highlight this drawback in the design of the Supporting Factor and to provide evidence showing it. Note that the current Commission's proposal to maintain the Supporting Factor and to extend its scope with no upper limit[31] is a way to resolve this drawback of the current scheme.

Overall, we find that the effect of the SF is highly heterogeneous and that not all SMEs with eligible exposures have benefited from its implementation. Our findings show that the SF has mainly benefited to small or micro enterprises, to firms with no Banque de France credit rating as well as to firms with rather small exposures. Interestingly, micro, small and non-rated firms are presumably the most credit constrained in terms of asymmetry of information in obtaining access to external finance and those for which a marginal euro of additional credit has the highest value. The SF has thus boosted the credit supply toward firms which presumably face the most severe credit constaints.

[31] More specifically, a new threshold at €2.5M instead of €1.5M is announced, with an additional Supporting Factor of 15% CRs reduction for the remaining part of SMEs' exposure.

Table 1.6: The effect of the SF on the credit supply: breakdown by exposure buckets

	Logarithm of the total outstanding amount of credit					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible · Post · *Small*	0.155***	0.159***	0.157***	0.059***	0.092***	0.038***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.006)
Eligible · Post · *Medium*	-0.116***	-0.112***	-0.118***	-0.127***	-0.112***	-0.074***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.009)	(0.006)
Eligible · Post · *Large*	-0.151***	-0.149***	-0.153***	-0.159***	-0.149***	-0.036***
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.008)
Observations	16,544,487	16,544,487	16,544,487	16,488,568	16,488,568	16,488,568
Adjusted R-squared	0.362	0.365	0.365	0.768	0.768	0.768
Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Size*Time FE	No	No	No	No	Yes	Yes
Group-specific trends	No	No	No	No	No	Yes

This table reports the estimates associated with the difference-in-differences specification (1.5). The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total eligible outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable *Eligible · Post* is the product of these two latter dummies. This variable is interacted with 3 buckets of exposures: Small, Medium and Large. *Small* exposures refer to exposures with an average pre-reform total outstanding amount of credit in [0-€500,000]. *Medium* exposures refer to exposures with an average pre-reform total outstanding amount of credit in [€500,000-€1,000,000]. *Large* exposures refer to exposures with an average pre-reform total outstanding amount of credit in [€1,000,000-€1,500,000]. All regressions control for size, rating, geographic location and industry classes, as well as year-quarter FEs. Column (1) displays results associated with these most basic FE. Columns (2) to (6) display estimates including respectively bank, bank-time, firm and size-time FEs as well as group-specific trends. Standard errors are clustered at the firm level. Clustered standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

1.6 Conclusion

This chapter investigates the effectiveness and the consistency of a new regulatory tool implemented specifically to promote SMEs' access to bank credit: a targeted reduction in bank CRs associated with SMEs loans. In particular, the objectives of this reform are to provide an easier access to bank credit for SMEs and to ensure adequate capital requirements for SME credit risk. That is why we examine this policy experiment along with these two dimensions.

First, the consistency of the reform regarding the intrinsic riskiness of SMEs is assessed through the computation of banks' economic capital requirements using the structural credit risk framework underlying the computation of the regulatory capital requirements. This method allows us to compute the contribution of each size class to the total risk of the portfolio, taking into account the potential diversification or concentration effects within the portfolio. We finally compare the "economic" CRs resulting from our multifactor model with the regulatory ones, with and without considering the reduction associated with the SF. We find that for each size class, the level of the regulatory CRs is far superior to the level of the economic CRs, even after the application of the SF. Overall, after considering the uncertainty surrounding these estimates and adopting a conservative approach, we find strong evidence that the SF is consistent with the difference in economic CRs between SMEs and large corporates.

Then, the impact of the reform on the credit supply to targeted SMEs is estimated through the difference-in-differences methodology. We thus compare the evolution of the outstanding amount of credit of eligible and ineligible exposures after the reform (vs. before the reform). We find evidence showing that the SF has been efficient in supporting bank lending to targeted SMEs. Specifically, we find that the magnitude of the effect of the SF has increased over time: the effect was almost zero in the first year after the entry into force of the SF but it has then intensified to reach a magnitude of 8% to 10% two years after the entry into force. As for the possible sources of heterogeneity, results indicate that the effect of the SF is much stronger on eligible exposures of small and micro enterprises than those on medium-sized enterprises. Then, we find convincing evidence showing that exposures of SMEs with no Banque de France credit rating tend to be more affected by the implementation of the SF than exposures of SMEs considered as safe or risky according to their credit rating, the former rarely facing credit constraints while the latter remaining too risky even after considering the capital relief provided by the SF. Finally, we find that the smallest eligible exposures benefited the most from the SF (as compared to larger eligible exposures). This result indicates that the threshold at €1.5 million can provide adverse incentives to banks regarding exposures slightly below the threshold. Overall, this supports the removal of the threshold as it is planned in the new version of the SF to come.

Appendices of Chapter 1

1.A French national credit register: breakdown by loan type

- Short-term loans (i.e. with an initial maturity shorter than 1 year)
  - Overdrafts on ordinary account (including short term credit line drawdown)
  - Accounts receivable financing
  - Factoring
  - Other short-term loans
- Medium and Long-term loans (i.e. with an initial maturity longer than 1 year)
  - Export credits
  - Other medium and long-term loans
- Financial Leases and Leasing
  - Equipment leases
  - Property leases
- Securitized loans
- Undrawn credit lines
  - Undrawn loans (of which factoring available)
  - Opening of documentary credit
- Guarantees commitments

1.B Risk analysis: data restrictions

This appendix reports more detailed information about the databases used in the *risk* analysis. To do that, we need to restrict the sample of firms to the following conditions:

– Firms must have exposures in the French credit register. In France, every bank should declare business loans provided that the loan amount is over €25,000 starting from 2006. However, before 2006, this threshold was €75,000. To avoid creating artificial entries of firms in 2006, we apply the €75,000 threshold over the entire sample period considered, *i.e.* 2004-2015.

– The Banque de France rating directorate gives to these firms a rating (including a default grade). This includes firms with annual turnover above €0.75 million and firms obtaining credit from at least one large banking group operating in the French loans to businesses market.

– We also exclude exposures toward the financial sector. By this way, we neutralize a break related to the end of the reporting of interbank exposures with non-resident counterparts in 2006.

– We exclude exposures toward individual entrepreneurs. They stopped reporting their exposures within the credit register in 2012, so we drop them from the total sample to avoid artificial exits of the sample.

1.C Credit analysis: data restrictions

This section reports more detailed information about the databases used in the *credit* analysis. To do that, we need to restrict the sample to the following conditions:

- We restrict the sample to the 7 largest banking groups operating in France. The other credit institutions of the sample are very specific credit suppliers that do not reflect bank lending in France. We thus keep the following banking groups: BNP-Paribas, Société Générale, BPCE, Crédit Agricole, Crédit Mutuel, HSBC, la Banque Postale, which represents 90% of the corporate lending market.

- Firms are restricted to SMEs according to the sole turnover criterium, *i.e.* we only keep firms with an annual turnover lower than €50 million. As mentioned above, the identification of SMEs can be tricky. For instance, 80% of legal entities constituted by 50 employees belong to a larger group. Therefore, to avoid any misclassification of companies, we restrict the sample to independent firms only, *i.e.* firms that are not affiliated with a corporate group.

- We exclude exposures toward the financial sector, the real estate sector, the public sector and the non-profit sector. We also drop holding companies.

- We exclude exposures toward individual entrepreneurs. They stopped reporting their exposures within the credit register in 2012, so we drop them from the total sample.

- In order to run clean specifications, we drop firms whose SME status or eligiblity status vary over the period. There, the aim is to keep firms for which the status remains constant over time (additional information on this important point can be found in Section 1.4.2).

1.D Institutional framework of the Supporting Factor reform

Definition of SMEs for the purpose of the Supporting Factor

The identification of SMEs is precisely defined by the 2003 European Commission Recommendation as follows: "*The category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding €50 million or an annual balance sheet total not exceeding €43 million.*" Among these criteria, the CRR indicates that only the annual turnover must be considered to qualify a company as an SME allowed to benefit from the SF.

Conditions of eligibility

Regarding the amount "owed" to the institution, the CRR also brings precisions about exposures eligible to the SME-SF. In the case of a credit line, only the drawn amount must be considered as regard to the €1.5 million compliance limit. However, provided that all conditions are met, the exposure as a whole, including its undrawn part will benefit from the capital relief. Thus, there exists a discrepancy between (i) the exposure amount considered for the eligibility to the SF and (ii) the exposure amount that will benefit from the CRs deduction (SF enforcement). Practically, off-balance sheet exposures and claims or contingent claims secured on residential property collateral must not be considered when assessing the amount owed and eligible to the SF. Though, the SF, as deduction in CRs, applies to the entire bank's exposure.

1.E Descriptive statistics

Table 1.E.1: Descriptive Statistics - Distribution of the outstanding amount of loans

N	Mean	SD	P10	P25	Median	P75	P90
Sample including firms whose eligibility status changes over time							
18 599 438	145.40	247.37	0.00	25.00	36.00	70.00	154.00
Sample of firms whose eligibility status is constant over time							
18 369 085	130.97	195.50	0.00	25.00	36.00	69.00	149.00
Before the implementation of the SF							
10 391 672	129.19	192.84	0.00	25.00	36.00	68.00	147.00
After the implementation of the SF							
7 977 413	133.30	198.88	0.00	25.00	35.00	69.00	151.00

This table provides descriptive statistics on our dependent variable, the total outstanding amount of loans. The samples described are before and after the implementation of the SF.
Source: Banque de France, French national Credit Register and authors' calculations.

Table 1.E.2: Descriptive Statistics

Eligibility Status	Frequency	Percent
	Before the implementation of the SF	
Non eligible (Exposures > €1,5M)	17,437	0.17
Eligible (Exposures < €1,5M)	10,374,235	99.83
Total	10,391,672	100.00
	After the implementation of the SF	
Non eligible (Exposures > €1,5M)	17,907	0.22
Eligible (Exposures < €1,5M)	7,959,506	99.78
Total	7,977,413	100.00

This table shows the distribution of eligible and non eligible exposures, for the two periods before and after the implementation of the SF.
Source: Banque de France, French national Credit Register and authors' calculations.

1.F Banque de France ratings and default rates

Table 1.F.1: Quasi default rates across Banque de France ratings

Classification	Banque de France Rating	Default 1	Default 2	Default 1		
		All firms		Medium-sized	Small	Micro
Safe (Investment Grade)	3++	0.10%	0.05%	0.02%	0.15%	.
	3+	0.31%	0.19%	0.03%	0.37%	0.23%
	3	0.44%	0.28%	0.42%	0.41%	0.54%
	4+	1.48%	0.97%	1.25%	1.55%	1.39%
	4	3.76%	2.16%	2.41%	3.73%	4.04%
No unfavorable information	No rating	4.54%	2.73%	6.37%	7.10%	4.52%
Risky (Speculative Grade)	5+	6.98%	3.26%	5.66%	7.39%	6.67%
	5	12.71%	8.00%	8.60%	12.49%	12.99%
	6	14.02%	10.45%	15.98%	16.19%	13.88%
	7	58.85%	12.59%	66.67%	60.51%	58.65%
	8	72.01%	16.23%	87.69%	68.01%	72.53%
	9	79.60%	19.59%	79.59%	83.25%	79.16%
	P	96.77%	95.84%	60.61%	78.82%	97.09%
Total		11.37%	9.11%	2.99%	5.59%	12.15%

This table reports quasi default rates broken down by Banque de France ratings. We build these quasi default rates at a one year horizon. The first definition of default (*Default 1*) is a dummy variable taking the value of 1 as soon as a firm received the ratings Banque de France for which at least one trade bill payment incident has been reported. The second definition of default (*Default 2*) is more restrictive and is a dummy taking the value of 1 as soon as a firm is the subject of insolvency proceedings (recovery or judicial liquidation proceedings). The default rates are computed over the entire period. The table reads as follows : 0.10% (resp. 0.05%) of the firms having a rating Banque de France 3++ over the pre reform period will be in defaults one year later.

Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

1.G Risk analysis: the detailed methodology

The computation of banks portfolio risk under the Basel regulatory framework derives from the structural credit risk approach proposed by Merton (1974). We use an extended version of this approach in order to assess the risk increase induced by the SF. In this section we provide a short description of this framework and describe how we apply it for our risk analysis.

In the Merton (1974) framework, losses at the sub-portfolio level are defined as the sum of losses on defaulting loans. Thus, if u_i is defined as the loss given default (LGD) of obligor i and Y_i is the default indicator variable of obligor i (Y_i takes the value of 1 if there is a default and 0 otherwise), total portfolio losses L are given by

$$L = \sum_{i=1}^{n} u_i Y_i \tag{1.G.1}$$

where n denotes the number of obligors.

In structural credit-risk models, default occurs if the financial health of borrower i crosses a default threshold. Here, financial health is represented by a latent (unobservable) variable U_i, which is determined by the realizations s of a set of S multivariate Gaussian systematic risk factors with loadings w_i and correlation matrix R, and the realization of a standard normal specific factor ε_i. Denoting Φ the standard normal cdf, default occurs when U_i crosses downwards a threshold. This threshold is calibrated from the borrower's historical default probability $\bar{p}_i$:

$$Y_i = 1 \Leftrightarrow U_i = w_i' S + \sqrt{1 - w_i' R w_i}\varepsilon_i < \Phi^{-1}(\bar{p}_i) \tag{1.G.2}$$

Specific risk factors ε_i are assumed to be uncorrelated among obligors and also independent from the systematic factors S. The factor loading can be interpreted as the sensitivity of the obligor i to systematic factors or more commonly expressed as the general macroeconomic state of the economy.

Thus, given a realization s of the systematic risk factors, Equation (1.G.2) can be rewritten such as a default occurs when:

$$\varepsilon_i < \frac{\Phi^{-1}(\bar{p}_i) - w_i' s}{\sqrt{1 - w_i' R w_i}} \tag{1.G.3}$$

As the borrower's specific risk factor is normally distributed, the default probability conditional to s is also standard normal. Moreover, assuming that specific risk can be entirely diversified away, losses can be approximated by their expected value conditional to s (see Gordy (2003)). Conditional portfolio losses are then defined by:

$$L(s) \approx \sum_{i=1}^{n} u_i \Phi \left[\frac{\Phi^{-1}(\bar{p_i}) - w_i' s}{\sqrt{1 - w_i' R w_i}} \right] \tag{1.G.4}$$

This framework is known as the asymptotic multi-factor framework of credit risk (see Lucas et al. (2001)) and is an extension of the asymptotic latent single risk factor (ASRF) model underlying the Basel II CRs for credit risk. Equation (1.G.4) assumes that each obligor can be characterized by his individual default threshold and factor sensitivities. However, in retail loan portfolios, default rates are generally computed based on rating grades, and sensitivities to risk factors cannot be computed on an individual basis. Thus, assumptions are required to reduce the number of parameters of the loss variable. A common assumption is that obligors who belong to the same rating j will share the same default threshold. Moreover, one could assume that the vector of risk factor sensitivities is the same for obligors sharing a set of common characteristics. Assuming that the portfolio is portioned in K segments (here the firm size), that credit exposures are rated using a scale with J grades, and denoting n_{kj} the number of exposures with rating j in segment k, losses can be rewritten as:

$$L(s) \approx \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{i=1}^{n_{kj}} u_i \Phi \left[\frac{\Phi^{-1}(\bar{p_j}) - w_k' s}{\sqrt{1 - w_k' R w_k}} \right] \tag{1.G.5}$$

The calibration of this credit risk model requires the estimation of J default thresholds $\Phi^{-1}(\bar{p_j})$ of the rating scale, the factor loadings w_k, and the correlation matrix R. A first order choice is the specification of the systematic risk factors. However, we are interested in capturing the risk heterogeneity for firms of different sizes. Thus, we expand the latent factor approach underlying the ASRF model by considering a latent risk factor for each size class. These factors are possibly correlated, with correlation matrix R. In other words, we consider that credit risk within each portfolio size segment can be described by a single risk factor model, taking into account correlations of risk exposures across segments. The different parameters are estimated using a binomial probit generalized linear mixed model (see McNeil and Wendin (2007b)). The generalized linear mixed model (GLMM) provides a straightforward econometric framework to estimate the parameters of our multifactor credit risk model. Indeed, the choice of this specification leads to consider the default thresholds as fixed effects and the factor loadings and factor correlations as described by a multivariate vector of Gaussian random effects.

Within the framework of GLMM models, the default probability in Equation (1.G.5) is defined as follows. Let Y_t be an $(N \times 1)$ vector of observed default data at time t and γ_t be the $(K \times 1)$ vector of random effects. The conditional expected default probability of obligor i at time t is then:

$$P(Y_{ti} = 1|\gamma_t) = \Phi(x'_{ti}\beta + z_i\gamma_t) \tag{1.G.6}$$

where $\Phi(.)$ is the standard normal cdf[32], β denotes the vector of parameters associated with the fixed effects (the borrower's rating class) and z_i is the design matrix of the random effects, here an identity matrix with size the number of random effects. If the rating scale is properly built, we expect the β parameters that correspond to the default thresholds to be associated with the ratings to be ordered and to increase as credit quality decreases. $x'_{ti} = [0, ..., 1, ..., 0]$ is a $(1 \times J)$ vector of dummies defining the rating of borrower i at time t.

Once the credit risk parameters are estimated, the distribution of losses at the portfolio level is computed by Monte Carlo simulations, with each simulated realization of the systematic risk factors being converted into a conditional default probability at the rating/size segment level as defined by Equation (1.G.5) and, finally, into conditional expected losses at the portfolio level. Various quantiles based on risk measures such as Value-at-Risk (VaR) or Expected Shortfall can then be retrieved from the simulated distribution of portfolio-wide losses.

Our multifactor model provides the economic capital necessary to cover losses of a portfolio of loans by firm size buckets. We use this model as a benchmark to check whether the capital deduction induced by the Supporting Factor on SME loans (about 24%) is consistent with the difference in economic capital between the SME loans and the rest of the corporate loans portfolio (the "large" corporate businesses).

[32] We focus on the probit link function because the normal distribution is the underlying link function that is assumed by the Basel II/III framework of credit risk.

* * *

Chapter 2

Determinants of banks' liquidity: a French perspective on interactions between market and regulatory requirements

* * *

This chapter investigates the impact of solvency and liquidity regulation on banks' balance sheet structure. It contributes in particular to the debate on the use of liquidity buffers by banks, as initiated by Goodhart (2010)'s "last taxi" argument. Indeed, during crisis periods, interactions between funding and market liquidity, as well as regulatory constraints, put into question the banks' response to liquidity shocks. According to a simple portfolio allocation model, we find that banks' liquidity increases when the regulatory constraint is binding, leading banks to hoard liquidity, which is not the case when their regulatory constraint is not binding. Using the regulatory "liquidity coefficient" implemented in France ahead of Basel III's Liquidity Coverage Ratio, we then provide empirical evidence of interaction between banks' liquidity and market liquidity. In times of stress, measured by financial variables capturing international markets' risk aversion and tensions in the interbank market, French banks actually decreased their liquidity coefficient, indicating that the regulation was initially not binding, with a transmission channel materialising mainly on the liability side. We also emphasize strong interaction between regulatory liquidity and solvency with a positive effect of the solvency ratio on the liquidity coefficient, while the reverse is not true.

* * *

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2.1 Introduction

The 2008 Global Financial Crisis highlighted the risk related to banks' liquidity, a field that had not been addressed at the international regulatory level before. The difficulties faced by adequately capitalized banks revealed the importance of banks' liquidity positions, given that liquidity risks may arise from different components and interactions. Indeed, when investors start losing confidence in the solvency of an institution, they withdraw their short-term deposits and raise margin calls, undermining banks' ability to meet their commitments. The rise in funding costs might force the bank into fire sales, triggering a fall in their market prices. The loss of funding jointly with the decline in market prices, results in large losses for the institution, endangering its solvency. In addition to interactions between banks' liquidity and solvency, interactions between funding liquidity[1] and market liquidity[2] also raise concerns about an appropriate regulatory liquidity framework.

In the new Basel III regime, a liquidity regulatory framework has been agreed for the first time upon at the international level, with the introduction of two liquidity ratios. The Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) pursue complementary objectives, which are to promote the short-term resilience of banks' liquidity profile and to maintain a stable funding profile, respectively. While the latter has not yet entered into force, the former has already been implemented progressively since 2015. The LCR is designed to ensure that banks withstand a 30-day liquidity stress scenario. Against this background, this chapter aims at assessing how banks adjust their liquidity and the structure of their balance sheet when facing a liquidity shock while staying compliant with regulation.

Although supervisors have been paying increasing attention to the sensitivity of the banking liquidity since the crisis, assessment of the liquidity regulation is still at its infancy, due

[1] The funding liquidity is defined as the ability of a financial institution to meet its own financial obligations by raising funds in the short term.

[2] The market liquidity measures the capacity to sell an asset without incurring a market price change.

to different factors. Data confidentiality constrains researchers to focus on proxies from publicly available data. When available, data is limited to short time series due to the recent introduction of the global liquidity regulation. In this context, our study provides several contributions to the literature. First, we use data on a long-established regulatory liquidity ratio, close to the LCR, imposed on French banks since 1993, *i.e.* ahead of Basel III, instead of proxies. Second, we shed light on the interactions between market and funding liquidity. In particular we address the issue of the use of liquidity buffer in crisis times, as initially discussed by Goodhart (2010), who argued that banks should be allowed to use their liquidity buffers.[3] Indeed, during a crisis, due to interactions between funding and market liquidity, as well as regulatory constraints, banks may either increase or decrease liquidity. In particular, Hong et al. (2014) show that LCR increased during the Global Financial Crisis, as banks hoarded liquidity. More specifically, we estimate how funding liquidity reacts to market liquidity from a quantity perspective, instead of a price perspective as mostly seen in the literature. Indeed, data on internal transfer prices for the funding of individual transactions are most of the time not available. Finally, we also capture the potential interactions between solvency and liquidity regulation, and assess banks' reactions to liquidity shocks.

To this end, we develop a simplified theoretical model to illustrate the impact of the introduction of liquidity regulation on banks' behavior. We maximize the profit of a representative bank under liquidity and solvency constraints in order to highlight banks' liquidity positions when interacted with market liquidity. Specifically, the model indicates that when regulation is binding or market liquidity is low, banks adopt a precautionary behaviour and accumulate liquidity to cope with future liquidity shocks: banks accumulate marketable securities, rather than risky loans that constitute unavailable liquidity. On the other hand, when banks are more than compliant with the liquidity constraint, so that regulation is not binding, they choose their allocation of more or less liquid assets depending on their profitability, diversifying their portfolio according to Markowitz theory.

In line with the theoretical model, we present empirical evidence that variables reflecting market liquidity affect regulatory liquidity and solvency ratios only during periods of high market stress. In particular, this negative effect of market liquidity is larger on the liquidity than on the solvency ratio, confirming the evidence of strong interactions between market liquidity and bank funding liquidity during crisis periods. We also emphasize interactions between liquidity and solvency ratios. We show that a higher level of solvency enables the

[3] Goodhart (2010) makes a comparison between standing liquidity buffers and a taxi waiting at a train station : "there is a story of a traveller arriving at a station late at night, who is overjoyed to see one taxi remaining. She hails it, only for the taxi driver to respond that he cannot help her, since local bye-laws require one taxi to be present at the station at all times!"

liquidity ratio to improve. Consistently, when disentangling the impact of the financial variables on the different components of the regulatory liquidity ratio, we find that the effect of liquidity market variables materializes mostly on the liability side of the liquidity coefficient, through net cash outflows.

Surprisingly, the impact of the banking group membership only affects the relationship between financial risk variables and the solvency ratio, failing to find evidence of liquidity management at the group level. Likewise, we find that commercial banks are the most affected by the financial variables on their regulatory ratios. To a lesser extent, the solvency ratios of mutual banks and financial firms are impacted by the VIX variable and the interbank spread variable, respectively.

Given the non-linear relationship between bank funding liquidity and market liquidity, the implementation of counter-cyclical regulation, promoting accumulation of liquidity in times of expansion and its use in times of crisis, such as the regulation of capital buffers, seems more appropriate to prevent future crises. Accordingly, the LCR as developed by Basel effectively takes this required counter-cyclical form and allows to fall below regulatory thresholds in case of economic stress to enable banks to use available reserves without any sanction from supervisors. Finally, our findings confirm the need to assess the combined effect of liquidity and solvency requirements, as these elements interact closely and produce combined effects.

The remainder of this chapter is organized as follows. Section 2.2 reviews the literature on liquidity risks and their effects. Section 2.3 presents the theoretical model while Section 2.4 is devoted to the empirical analysis. Policy implications and Impulse Response Functions methodology and application are discussed in Section 2.5. Section 2.6 concludes.

2.2 Literature review

The global financial crisis highlighted the crucial role of liquidity in the outburst of destabilising confidence effects. Berger and Bouwman (2017) provide evidence that high levels of bank liquidity creation help predict future crises. Hanson et al. (2015) highlight the large synergies between the asset and liability sides of the balance sheet. The stable funding structure of traditional banks provides them a comparative advantage for holding assets potentially vulnerable to transitory price movements. Likewise, Allen and Gale (2000) paper is a theoretical model where negative externalities associated with liquidity transformation may occur via interregional cross holdings of deposits. Interbank contagion arises when banks tend to hoard liquidity by holding more liquid assets than usually. In this context of increasing liquidity issues, Hong et al. (2014) show that banks' liquidity risks should be managed at both the individual level and the system level. It is thus important to assess the adjustments of banks' balance sheets related to the recent liquidity regulation. Despite the evidence related to the stakes of liquidity, the determinants of banking liquidity remain much less explored than those of banking capital, whose regulation has been implemented earlier. Some exceptions are Bonner et al. (2015) and de Haan and van den End (2011) who analysed the implications of regulation on the level of liquidity.

Following the seminal paper by Diamond and Dybvig (1983) explaining how bank runs can affect healthy banks, the liquidity regulation, through deposit insurance, received theoretical underpinnings. They point out the vulnerability arising from the liquidity transformation function performed by banks whereby they fund illiquid long-term assets with potentially unstable short-term liabilities. In their paper, Bonner and Hilbers (2015) provide an historic overview of the liquidity regulation. More recently, the impact of Basel III liquidity regulation has been assessed in terms of liquidity risk prevention as well as its overall macroeconomic impact. Theoretically, Van Den End and Kruidhof (2013) attempt to simulate the systemic implications of the *Liquidity Coverage Ratio*. However, empirically, most of studies focus on proxies of the regulatory liquidity ratios, such as *deposits over loans ratio* for Tabak et al. (2010), due to constraints on data confidentiality and availability. Among others, Roberts et al. (2018) use a *Liquidity Mismatch Index* to show evidence of reduced liquidity creation from banks that enforced the *Liquidity Coverage Ratio*. Similarly, Banerjee and Mio (2018) use the UK *Individual Liquidity Guidance* (ILG) ratio to study the effects of liquidity regulation on banks' balance sheet. Banks reacted to this liquidity regulation by increasing the share of high quality assets and non-financial deposits. They also reduced interbank/financial loans and short term wholesale funding, which is positive for the stability of the financial system. One of our contributions relies on the use of a *Liquidity Coefficient* officially enforced in France, which shares some similarities with the *Liquidity Coverage Ratio* (see Section 2.4.1.3), over the 1993-2014 period, *i.e.* including the Global Financial Crisis.

Another strand of the literature, relevant to our paper, highlights how liquidity and capital regulations interact. So far, supervisors have considered liquidity and solvency risks but these risks were often viewed as independent.

On the one hand, the consequences of the solvency regulation are still uncertain. While

Berger and Bouwman (2009) and De Nicolo et al. (2014) find heterogeneous effects depending on the size of the bank or the level of initial capital, some recent papers tend to indicate a negative impact of higher capital requirements on credit distribution (see Fraisse et al. (2020) for France, Aiyar et al. (2014) for the UK, Jimenez et al. (2017) for Spain or Behn et al. (2016) for Germany). Studying the effect of the introduction of liquidity regulation, combined with solvency regulation, could help to determine the answer to this question.

To this end, Schmitz et al. (2019) estimate empirically the interactions between solvency and funding costs and highlight four channels of transmission between the two risk components: uncertainty about the quality of assets, fire sales, bank profitability and bank solvency. Through a theoretical model, Kashyap et al. (2017) find that credit risk and run risk endogenously interact, showing that capital regulation generates more lending while liquidity regulation deteriorates it. Conversely, Adrian and Boyarchenko (2018) recommend liquidity requirements as preferable prudential policy tool relative to capital requirements. Indeed, while liquidity requirements reduce potential systemic distresses, without impairing consumption growth, capital requirements imply a trade off between consumption growth and distress probabilities. More broadly, several papers examine whether capital and liquidity appear as complements or substitutes (Distinguin et al. (2013), Bonner and Hilbers (2015)). Kim and Sohn (2017) examine whether the effect of bank capital on lending differs depending upon the level of bank liquidity. Bank capital exerts a significantly positive effect on lending only when large banks retain sufficient liquid assets. Extending the Diamond and Dybvig (1983) model, Acosta Smith et al. (2019), highlight a tradeoff between a "skin in the game" effect that induces banks to accumulate more liquid assets in order to protect their capital and the impact of a more stable funding structure that may lead banks to shift their portfolio into more higher yielding illiquid assets. They show that the latter effect dominates the former in the UK so that the two regulations may appear as substitutes. Likewise, DeYoung et al. (2018) find that U.S. banks with assets less than USD1 billion treated liquidity and capital as substitutes in response to negative capital shocks. In contrast, Faia (2018) and Kara and Ozsoy (2019) conclude that they are complementary. The former explain that capital requirements reduce banks' solvency region, while liquidity coverage ratios reduce the illiquidity region. The latter suggest that the enforcement of solvency requirements alone was ineffective in addressing systemic instability caused by fire sales. From another perspective, Cont et al. (2019) are among the few authors who develop a structural framework for the joint stress testing of solvency and liquidity in order to quantify the liquidity resources required for a financial institution facing a stress scenario. Given the existence of conflicting pieces of evidence, further work is needed to design an appropriate framework including capital and liquidity interactions.

Moreover, liquidity risks strongly interact with other risks, giving rise to amplification mechanisms. In particular, Brunnermeier and Pedersen (2007), as well as Drehmann and Nikolaou (2013), show how market and funding liquidity interact. The authors demonstrate that market liquidity is highly sensitive to further changes in funding conditions during liquidity crises and suggest that central banks can help mitigate market liquidity problems by controlling funding liquidity. We shed light on the relationship between market liquidity and funding liquidity by studying the impact of market liquidity indicators such as aggregate financial risk variables (VIX index and interbank spreads) on banking liquidity via the liquidity coefficient. This interaction enables us to understand how liquidity mechanisms work and how contagion arises.

Against this background, this chapter brings several contributions to the literature. To the best of our knowledge, this is one of the few papers using data on a long-established regulatory liquidity ratio, close to the LCR, imposed on French banks, instead of using a market -or balance sheet- based proxy. Moreover, our research focuses on interactions between liquidity and solvency as well as between market and funding liquidity. More particularly, this study estimates funding liquidity at the individual bank's level from a quantity perspective (a liquidity ratio), instead of an aggregate price perspective (funding costs) as mostly seen in the literature. Basing our estimations on a regulatory ratio rather than on market prices, we consider our strategy to be complementary and more robust as market prices might get distorted by market sentiment or other exogenous factors. Finally, the chapter implement a liquidity stress-test through Impulse Response Functions.

2.3 Theoretical model

2.3.1 Set-up of the model and assumptions

The main objective of our model is to assess how banks react to liquidity shocks. We study the determinants of bank's liquidity and its interaction with market liquidity. Our model is based on a representative bank that maximizes its profit under balance sheet, capital and liquidity constraints.

Two sources of financing are available to the bank: equity capital, denoted K; and debt D, remunerated at the rate r^d. Depending on the state of the economy, a fraction α of deposits is withdrawn.

There are two items on the asset side: loans L, with a long-term maturity and a return r^l; and marketable securities G, whose return r^g is equal to the risk-free rate. We assume the following inequalities: $r^d < r^g < r^l$. Loans are considered to be riskier and, thus, provide a higher rate of return. It can be illustrated by a look at the structure of a bank's balance sheet:

<table>
<tr><td colspan="2">$Assets = A$</td><td colspan="2">Liabilities =LBT</td></tr>
<tr><td>L</td><td>r^l</td><td>D</td><td>r^d</td></tr>
<tr><td>G</td><td>r^g</td><td>K</td><td>r^k</td></tr>
<tr><td colspan="2">$Total = A$</td><td colspan="2">$Total = A = LBT$</td></tr>
</table>

Bank's profit. The bank is assumed to behave as a mean-variance investor with risk aversion coefficient γ. The profit can be written as the following, with a risk-return arbitrage term as in Freixas and Rochet (2008) and in Fraisse et al. (2020), among others:

$$\max_{G,L,D} \pi = r^l L + r^g G - r^d D - \frac{\gamma}{2}(\sigma_G^2 G^2 + 2\sigma_{GL} GL + \sigma_L^2 L^2) \tag{2.3.1}$$

with σ_G^2 and σ_L^2 corresponding to the variance of returns on securities and loans, respectively, and σ_{GL} the covariance between the returns on securities and loans.

Bank's constraints. The bank faces three different constraints.

- The first one is a **balance sheet** constraint:

$$D + K = L + G \tag{2.3.2}$$

For a given level of total assets, this balance sheet constraint implies that the larger the capital K, the lower the debt D, hence the lower the risk of deposit outflows. From that point of view, solvency regulation, which aims at increasing K, and liquidity regulation, which aims at reducing D, may appear as substitutes. However, we will see below that they may arise more complementary than substitutable.

- The second one is a **solvency** constraint, assimilated to a leverage constraint:

$$K \geq \eta D \qquad \text{with} \quad 0 < \eta < 1 \tag{2.3.3}$$

and with $\frac{\eta}{1+\eta}$ the ratio of capital to total assets, i.e. the leverage ratio.

Assuming that the solvency constraint is binding, the balance-sheet constraint becomes:

$$D(1+\eta) = L + G \qquad \Leftrightarrow \qquad D = \frac{1}{1+\eta}(L+G) \tag{2.3.4}$$

- The third one is a **liquidity** constraint, close to the LCR regulatory definition:

$$\beta\ G + (1-\beta)\ \phi\ G \geq \alpha\ D \tag{2.3.5}$$

where β is the share of marketable securities maturing, so that $(1-\beta)$ measures the average bank's holdings of bonds. Liquidating bonds implies a haircut of $(1-\phi)$, hence ϕ is the fraction of the book value of the securities which were not maturing at t, i.e. a measure of the liquidity of the bank's marketable securities which is state-dependent. α denotes the outflow rate on the liabilities.

Another interpretation of the liquidity constraint (2.3.5) is to ensure that banks accumulate enough liquid assets be able to cope with net cash outflows (deposit outflows, debt roll-off). To cope with deposit withdrawals at time t, the bank must sell marketable securities to get cash. However, depending on the market liquidity and the state of the economy, marketable securities are not necessarily sold at their book value, which affects the bank's liquidity position.

After combining the expression of D given by (2.3.4) into (2.3.5), the liquidity constraint gives the following inequality :

$$\beta\ G + (1-\beta)\ \phi\ G \geq \frac{\alpha}{1+\eta}\ (L+G) \tag{2.3.6}$$

$$[\frac{(\beta + (1-\beta)\phi)(1+\eta)}{\alpha} - 1]\ G \geq L \tag{2.3.7}$$

This is equivalent to:

$$(B-1)\ G \geq L, \tag{2.3.8}$$

with

$$B = \frac{(\beta + (1-\beta)\phi)(1+\eta)}{\alpha}. \tag{2.3.9}$$

2.3.2 The programme of the bank

We are interested in identifying the determinants of the share of marketable securities G. The bank maximizes its profit; its variables of choice are G, L and D, conditional on a level of total liabilities ($K + D$, assuming the leverage constraint holds):

$$\max_{G,L,D} \pi = r^l L + r^g G - r^d D - \frac{\gamma}{2}(\sigma_G^2 G^2 + 2\sigma_{GL} GL + \sigma_L^2 L^2) \tag{2.3.10}$$

subject to the transformed liquidity constraint:

$$(B-1)\ G \geq L \tag{2.3.11}$$

and

$$L + G = A \Leftrightarrow L = A - G \tag{2.3.12}$$

with A being the amount of total assets. Substituting (2.3.12) into (2.3.11), one gets:

$$(B-1)\ G \geq A - G \Leftrightarrow G \geq \frac{A}{B}, \tag{2.3.13}$$

so that the following condition necessarily holds:

$$A \geq G \geq \frac{A}{B} \tag{2.3.14}$$

We can associate the following Lagrangian function, with D and A exogenous:

$$\begin{aligned} \mathcal{L}(G) \quad = \quad & r^l(A - G) + r^g G - r^d D \\ & -\frac{\gamma}{2}\Big(\sigma_G^2 G^2 + 2\sigma_{GL} G(A - G) + \sigma_L^2 (A - G)^2\Big) \\ & +\lambda(G - \frac{A}{B}) \end{aligned} \tag{2.3.15}$$

with λ the Lagrange multiplier of the liquidity constraint.

The first-order condition of the Lagrangian on G is the following:

$$\frac{\partial \mathcal{L}}{\partial G} = 0 \Leftrightarrow -r^l + r^g - \frac{\gamma}{2}\Big(2\sigma_G^2 G + 2\sigma_{GL}(A - 2G) - 2\sigma_L^2(A - G)\Big) + \lambda = 0 \tag{2.3.16}$$

$$\Leftrightarrow r^g - r^l - \gamma(\sigma_G^2 - 2\sigma_{GL} + \sigma_L^2)G - \gamma(\sigma_{GL} - \sigma_L^2)A + \lambda = 0 \tag{2.3.17}$$

After solving the first-order condition, we get the following expression of G:

$$G^* = \frac{r^g - r^l - \gamma A(\sigma_{GL} - \sigma_L^2) + \lambda}{\gamma(\sigma_G^2 + \sigma_L^2 - 2\sigma_{GL})} \tag{2.3.18}$$

Similarly, using equation (2.3.12):

$$L^* = \frac{\gamma A(\sigma_G^2 - \sigma_{GL}) - r^g + r^l - \lambda}{\gamma(\sigma_G^2 + \sigma_L^2 - \sigma_{GL})} \tag{2.3.19}$$

These two equations indicate that when the liquidity constraint is binding (λ>0), the demand for G increases and the demand for L decreases. The liquidity constraint in equation (2.3.14) is more likely to be binding when B is low.

We also observe that $\frac{\partial B}{\partial \phi} = \frac{(1-\beta)(1+\eta)}{\alpha} > 0$ and $\frac{\partial B}{\partial \alpha} < 0$. Indeed, the lower the market liquidity (ϕ) or equivalently the higher the expected haircut (1-ϕ), the more banks accumulate marketable assets G to meet deposit withdrawals. Similarly, the higher the outflow (α), the more banks accumulate liquid assets G, also to meet deposit withdrawals.

According to the model, two main hypotheses are therefore possible, depending on whether the liquidity constraint is binding:

Hypothesis 1: *The liquidity constraint is not binding ($\lambda = 0$); in the worst occurences of the state of nature, banks may reduce their liquidity ratio.*

- During normal periods, deposit withdrawals (α) are small, or the haircut is small (ϕ high), so that B is large and A/B is small in (2.3.14). Thus, the liquidity constraint is not binding and we have an interior solution so that L and G are determined by the Markowitz portfolio. This means that the bank makes its portfolio choice based on the risk-return trade-off between loans L and marketable securities G.

- In the bad occurences of the state of nature, banks may sell liquid assets to offset deposit withdrawals, so that balance sheet size decreases and the banks' overall liquidity decreases. In that case, when the bank is facing a liquidity shock, the liquidity ratio decreases until the bank is constrained by the regulatory liquidity requirements.

Hypothesis 2: *The liquidity constraint is binding ($\lambda > 0$); in the worst occurences of the state of nature, banks hoard additional liquidity.*

- In this case, the liquidity constraint is binding, so that $G^* = A/B$. In periods of stress, deposit withdrawals (α) increase or the haircut rises (ϕ small), so that B decreases. The choice between L and G is thus twisted towards higher level of G than for the Markowitz portfolio, implying that banks are constrained to forego profit opportunities (as $r^g < r^l$) in order to stay compliant with the liquidity regulation.

  G is thus determined by the liquidity constraint and the solvency constraint.

Such a liquidity hoarding behavior in hypothesis 2 may be the consequence of regulation for which banks hoard liquidity to meet regulatory requirements.

Nevertheless, an alternative interpretation of hypothesis 1, where banks already quite liquid may accumulate liquidity buffers, for precautionary motives. This is the case when β is high, so that banks accumulate bonds with short maturity while liquidity regulation is not binding. Banks thus build up liquidity buffers to meet potential withdrawals arising in future crises. In turn, during stress periods, banks that were initially quite liquid use their liquidity buffers above the regulatory liquidity.

From model to data. The two conclusions of the model are therefore that *(i)* when the liquidity regulation is not binding, banks choose their holdings of loans and liquid assets according to their profitability and let decrease their liquidity position in periods of stress, and *(ii)* when the banks' liquidity constraint is binding, banks accumulate liquid assets in crisis times, in order to stay compliant with regulation, displaying a liquidity hoarding behaviour.

We now aim to verify empirically these hypotheses. Accordingly, the main variables of interest in our empirical model will be the bank's liquidity ratio, the bank's solvency ratio and a proxy for marketable securities' liquidity ϕ. The data analysis will enable us to confirm whether the liquidity constraint is binding or not and which hypothesis materializes.

2.4 Empirical analysis

2.4.1 Data and descriptive statistics

2.4.1.1 Data

Our estimations use data from multiple sources and cover the period from 1993 to 2014, on a quarterly basis. Our two dependent variables are the ***liquidity coefficient*** and the ***solvency ratio***, coming from the French Prudential Supervision and Resolution Authority (Banque de France/ACPR) databases. The Basel III Liquidity Coverage Ratio (LCR) is now the international standard for banking liquidity at the short-term horizon. Precisely, it is calculated as the ratio of the total amount of an institution's holdings of High Quality Liquid Assets to the Total Net Expected Cash Outflows over a 30-day horizon in a stress scenario. The different components are granted different weights: in the numerator, the more liquid and higher quality an asset, the higher weight it gets; in the denominator, the more runnable a liability item, the higher weight it is assigned to. Wholesale funding receives a conservative treatment under the LCR in terms of assumed run-off rates. After a phase-in period that started in 2015, the minimum required level of the LCR reached 100 percent in 2018. Given the recent implementation and phasing-in as well as the limited time coverage of data, an analysis focusing on this ratio might not be relevant. Nevertheless, a binding Liquidity Coefficient was enforced in France from 1988 to 2014 for all banking institutions. This indicator provides a much larger set of observations both in terms of periods and cross sections than the LCR. The definitions, similarities and differences between both ratios are presented in Section 2.4.1.3. The LCR, like the French liquidity coefficient, has been implemented at the solo or legal entity level, meaning that each subsidiary of a banking group has to report and to abide by it. While liquidity management is often carried out at the consolidated level in banking groups, analysing liquidity at the solo level might be more appropriate from an analytical point of view. Indeed, liquidity may not flow freely between the subsidiaries of a banking group and looking at liquidity on a purely consolidated level might bias the analysis by omitting particular behaviours (BCBS, 2013).

We also used the banks' solvency ratio to capture the interactions between liquidity and solvency risks. It is defined as the amount of a bank's own funds divided by the sum of its risk-weighted assets. However, the solvency ratio is only available on a semi-annual basis for the whole period. We therefore interpolated the series to obtain quarterly data for this variable. We can note that all the unit root tests implemented for the liquidity coefficient and the solvency ratio allowed us to reject the null hypothesis implying the presence of non-stationarity.[4] As a reminder, the regulatory liquidity coefficient must be above 100% while the solvency ratio must not be lower than 8%.

The liquidity coefficient and the solvency ratios are expected to have positive interactions: more capital means a larger share of stable funding, which is thus supposed to increase the liquidity coefficient. Conversely, in a liquidity crisis, a bank finds it more difficult and costly to get funding; the increase in its funding costs lowers its profits, meaning that a smaller amount of earnings can be retained to increase its own funds. Moreover, when facing a liquidity crisis, a bank may have to recourse to fire sales to get cash, which results in losses if the assets are marked-to-market, undermining the bank's solvency.

Our explanatory variables include the lagged liquidity and solvency ratios, aggregate financial risk indicators, macroeconomic variables, bank-specific control variables and a time dummy variable. The lagged dependent variables account for a possible autoregressive behaviour of the liquidity coefficient and the solvency ratio due to adjustments costs of liquid assets and capital. Here, we expect a positive sign.

Aggregate financial risk variables are taken from Bloomberg. These variables reflect the liquidity conditions in different markets (worldwide/European/national). They include:

- the Chicago Board Options Exchange SPX Volatility ***VIX*** Index, an indicator for worldwide risk aversion but also liquidity in international markets as liquidity is inversely correlated with volatility. We expect a negative sign on the coefficient of this variable in the liquidity equation as the higher the VIX index, the higher the investors' risk aversion, the lower market liquidity and thus the lower liquidity expected for banks;

- the ***interbank spread*** variable, taken as an indicator of the price of short-term debt, market sentiment in the short-term interbank market and bank default risk in the European markets. The choice of a market-wide spread instead of an individual spread allows us to mitigate endogeneity issues. Our spread is built as the spread between the 3-month interbank (Euribor) rate and the German sovereign 3-month bill rate, the latter being taken as the risk-free rate. We expect a negative sign on the coefficient of this variable as the larger the spread, the more expensive and difficult it is for banks to get funding, which is expected to result in deteriorated liquidity and solvency ratios.[5]

[4] Tests are available upon request.

[5] We also ran all our estimations including the ***bid-ask spread*** on the French sovereign 10-year debt, taken as an indicator of market liquidity for an asset making up a large share of French banks' balance sheet. However, given the lack of significance of this variable in our regresssions and its low volatility, we decided to not include it in the main specifications presented in this paper.

Macroeconomic variables are ***GDP growth*** and ***inflation rate***, on a year-to-year basis, taken from INSEE (French National Statistical Institution). Both variables are expected to have a positive effect on solvency and liquidity ratios as credit and liquidity risks decline in good economic times. However, the literature has shown the impact of precautionary motives, which might induce banks to improve their ratios in bad times, by increasing their reserves.

Bank-specific control variables are taken from the SITUATION database (French Prudential Supervision and Resolution Authority/Banque de France), with a quarterly frequency. They are all lagged to avoid endogeneity issues:

- the ***size*** variable corresponds to the market share of the bank in terms of assets. The ratio of each bank's assets to the total assets is meant to avoid spurious correlation stemming from a time trend in banks' assets. A negative sign is expected on the coefficient of this variable, as big banks have less incentives to constitute capital or liquidity buffers due to a lower risk aversion, in line with the too-big-to-fail implicit assistance, and due to their higher ability to diversify risks and access funding;

- the ***return on equity*** ratio is used in the solvency equation only as a proxy for the cost of equity. In order to delete some reporting errors in the dataset, we dropped observations with a return on equity ratio above 100% or below -100%, which seems unlikely to occur. The expected sign of this variable is negative, as a higher return on equity means that banks will find it more expensive to raise more capital;

- the ***retail*** variable captures the bank's business model, built as the ratio of transactions with non-financial customers to total assets. The sign of this variable is uncertain. On the one hand, deposits from non-financials, in particular retail deposits, are supposed to be a stable source of funding on the liability side, but on the other hand, loans to non-financial customers are not considered as liquid on the asset side.

We also included a dummy variable to deal with data characteristics: the ***d_2010*** time dummy variable takes the value 1 from 2010Q2 onward to capture the change in the definition of the liquidity coefficient variable. As the definition of liquid assets was made stricter and the coefficients on cash outflows were increased at that time, we expect a negative sign on the coefficient of this variable. It also corresponds to the period in which the new Basel 3 franmework was announced.

Our models are estimated on a quarterly basis. Therefore, we calculated simple quarterly averages for series having a higher frequency, namely financial variables and the consumer price index.

2.4.1.2 Descriptive statistics

This subsection provides descriptive statistics about the dependent variables we used, namely the liquidity coefficient and the solvency ratio, as well as other financial and macroeconomic variables, described in Table 2.1. The French liquidity ratio (called "liquidity coefficient") is reported on a solo basis. Given the wide distribution of these variables, we decided to drop the 5th and the 95th percentiles of the sample for the liquidity coefficient and the solvency ratio, in order to address the misreporting issues and eliminate outliers. We also dropped observations equal to 0 that would reflect specific business models. We finally dropped banks with less than 5 observations (quarters) in the sample. We end up with an unbalanced data panel comprising 725 banks, 102 periods and more than 23,000 observations. In spite of this data cleansing, Table 2.1 shows a large dispersion in the liquidity ratio. In particular, the liquidity ratio displays a 90th percentile value of 1,741% while the 90th percentile value of the solvency ratio is at 54%. The solvency ratio thus displays a more concentrated distribution. Nevertheless, both the solvency and the liquidity ratios present a minimum value above the requirement threshold, which means that during the whole period, the banks composing our sample were compliant with regulatory ratios enforced in France.

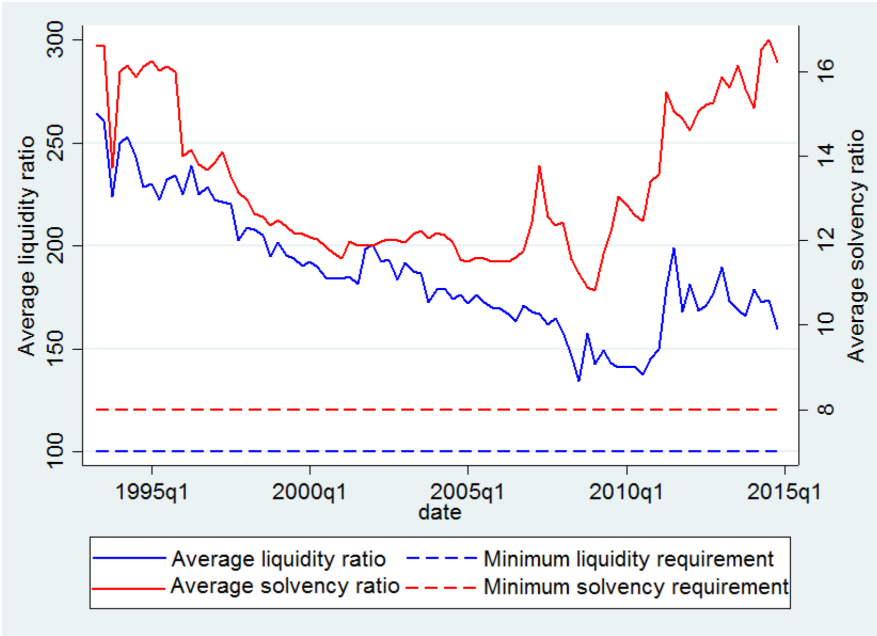
Table 2.1: Descriptive statistics of the main variables

VARIABLES	N	SD	P10	Median	Mean	P90
Liquidity ratio (in %)	25,611	2,306.57	127.18	225.87	907.23	1,740.87
Solvency ratio (in %)	25,611	21.19	9.82	15.58	24.64	53.97
Vix (in points)	25,611	7.48	12.44	18.53	19.89	29.30
Interbank spread (in %)	25,611	0.58	0.03	0.21	0.46	1.14
GDP growth (in %)	25,611	1.54	-0.11	1.88	1.71	3.37
Inflation (in %)	25,611	0.68	0.61	1.69	1.55	2.29

Table 2.1 presents descriptive statistics of the main variables used in the following estimations: the liquidity coefficient, the solvency ratio, the VIX index, the interbank spread, GDP growth and the inflation rate, on an unweighted average basis.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

The evolution of the average of the liquidity ratio and the solvency ratio are displayed in Figure 2.1. Overall, the liquidity and solvency ratios are usually not binding as the mean is always above the minimum requirements (dashed lines). In particular, the liquidity coefficient shows a continuous decline until 2010-2011, and a low level over the 2008-2011 period, characterized by a shortage of liquidity. Afterwards, liquidity picks up, with short run fluctuations until 2014. By contrast, the solvency ratio displays a rising trend from 2008.

Figure 2.1: Liquidity Coefficient and Solvency Ratio over 1993-2015



Note: the figure displays the evolution of the Solvency Ratio in red on the right-hand axis and the Liquidity Coefficient in blue on the left-hand axis, on a weighted average basis. The sample includes all French banking institutions, reporting over the period 1993 to 2015.
Sources: ACPR, Authors' calculations.

Finally, Table 2.2 displays correlations between all the variables composing our model. A positive and significant correlation coefficient can already be observed between the liquidity and solvency ratios (0.29). Furthermore, the latter are negatively correlated with the VIX index, the risk aversion indicator, but positively correlated with the interbank spread. Given that our financial variables are related to different markets and different risks, we consider that the risk of colinearity is limited. In this context, the empirical analysis will enable us to better assess these interactions between market liquidity and banking regulatory ratios.

Table 2.2: Correlations between the main variables

	Liquidity coefficient	Solvency ratio	Vix	Interbank	GDP	Inflation
Liquidity ratio	1.0000					
Solvency ratio	0.2882***	1.0000				
	(0.0000)					
Vix	-0.0225***	-0.0246***	1.0000			
	(0.0003	(0.0001)				
Interbank	0.0375***	0.0144**	-0.0246***	1.0000		
	(0.0000)	(0.0211)	(0.0001)			
GDP growth	0.0140**	0.0056	-0.2048***	-0.2259***	1.0000	
	(0.0247)	(0.3741)	(0.0000)	(0.0000)		
Inflation	0.0160**	0.0129**	-0.1645***	0.2023***	0.0379***	1.0000
	(0.0105)	(0.0393)	(0.0000)	(0.0000)	(0.0000)	

Table 2.2 presents correlation coefficients related to the main variables used in the following estimations: the liquidity coefficient, the solvency ratio, the VIX index, the interbank spread, GDP growth and the inflation rate. Standard errors are mentioned in brackets, as an indicator of confidence.
*** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

2.4.1.3 Liquidity coefficient, a good proxy for the LCR?

As mentioned above, the Liquidity Coverage Ratio has only been enforced since 2015. Although the LCR and the Liquidity Coefficient are both defined as ratios of liquid assets to net cash outflows over a 30-day period, there are some differences associated with the treatment of intragroup exposures and off-balance sheet items, as well as with the weights associated with the different components, with the LCR being stricter than the liquidity coefficient in terms of liquid asset definition. It is thus necessary to compare these ratios to assess to what extent our liquidity coefficient can be used as a proxy of the Liquidity Coverage Ratio in a regression.

The liquidity coefficient was implemented from 1988 to 2015 for all banking institutions, then interrupted and only reported by financial companies from 2015 to 2018. Although enforced from 2015, the LCR has been reported from 2010 to 2018. Thus, there is some overlap in the reporting of both the LCR and the liquidity coefficient by the same institutions, which enables us to assess the relationship between the liquidity coefficient and the LCR. We analyse these correlation in Table 2.3. We can see that the correlation between the LCR and the Liquidity Coefficient is positive and significant (0.19). When we disentangle the different components of the two ratios and consider their bilateral correlations, we can notice even higher correlation coefficients. This is the case with the numerators of the two ratios, namely the liquid assets, which display a correlation coefficient of 0.41, and with the denominators, namely the cash outflows, with a coefficient of 0.36. Both ratios are even more correlated when we consider them on a gross basis, i.e. before the application of regulatory weights to their different components, with a coefficient of 0.69. These results are in line with expectations, reflecting that the main differences between these ratios come from the application of different weights. This indicates a strong relationship between the liquidity coefficient and the Liquidity Coverage Ratio, which confirms the relevance of using the liquidity coefficient as a proxy of the LCR over an extended period of observations.

Table 2.3: Correlation between Liquidity Coefficient and Liquidity Coverage Ratio

	LCR	gross LCR	(LCR) Liquid assets	(LCR) Cash outflows
LC	0.1851***			
gross LC		0.6946***		
(LC) Liquid assets			0.4063***	
(LC) Cash outflows				0.3587***

Table 2.3 shows the correlation between the French Liquidity Coefficient (LC) and the Basel III Liquidity Coverage Ratio (LCR). Variables are expressed in ratio and in gross level terms.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Sources: ACPR, Authors' calculations.

2.4.2 Simultaneous equations method

One of the objectives of this study is to capture interactions between liquidity and solvency ratios. Therefore, we rely on the simultaneous equations regression using the Two Stage Least Squares (2SLS) estimator and fixed effects.[6] This methodology enables us to run a system of equations which are endogenous, when the dependent variable's error terms are correlated with the independent variables. Indeed, in each equation, the Liquidity Coefficient and the Solvency Ratio are endogenous variables on both the left and right hand sides of the equation.

[6] One could suggest the use of Three Stages Least Squares (3SLS) method that also accounts for cross correlation in error terms. In our case, the result of the Hausman test supports the use of the 2SLS methodology at the usual confidence level (tests are available upon request).

The reduced form of our simultaneous equations specification can be read as follows for bank i:

$$Y_{i,t} = \alpha_i + \phi Y_{i,t-1} + \beta X_t + \gamma Z_{i,t-1} + \epsilon_{i,t}$$

where Y is a vector of two endogenous variables (liquidity coefficient and solvency ratio); X is a vector of explanatory variables including aggregate financial risk variables (the VIX index and the interbank spread), macroeconomic variables (GDP growth and inflation) and dummy variables; Z is a vector of bank-specific variables (size, retail, return on equity ratio); α_i is a vector of individual bank fixed effects and ϵ the vector of error terms, with i referring to individual banks and t to time (quarters).

2.4.3 Results

This section presents the results associated with the different specifications we used. Our baseline estimation analysed the relationship between the liquidity coefficient, the solvency ratio and the set of explanatory variables previously defined. We then interacted some variables of this basic specification with specific dummies in order to capture non-linearities and to shed light on heterogeneous effects.

We first examine the baseline estimation, displayed in Table 2.4, showing a positive and significant interaction between the liquidity ratio and the solvency ratio. The first column refers to the liquidity coefficient equation, while the second one refers to the solvency ratio equation. Results indicate a positive and significant impact of the solvency ratio (5.20) on the liquidity coefficient, which provides evidence of positive interactions between solvency and liquidity. Precisely, when banks increase their solvency ratio by 1 percentage point in $t-1$, this is associated with a 5.20 percentage point increase in the liquidity coefficient at the following period. In the solvency equation, we find a coefficient of the liquidity ratio close to zero, although significant. Therefore, both variables are found to move in the same direction, but with a stronger effect of solvency on liquidity. We also observe a high value of the autoregressive coefficients, particularly for the solvency ratio (0.89), and to a lesser extent for the liquidity coefficient (0.63), reflecting some inertia for these variables, although we did not find any evidence of a unit root process.[7]

[7] Results for unit root tests are available upon request.

Overall, the aggregate financial variables are found to have no significant effect on the liquidity and solvency ratios. The absence of significant effect of these variables might be due to the fact that on average the period of observation (1993-2014) corresponds to a time of "great moderation" (apart from a few crisis years), during which financial variables displayed little volatility. This explanation will be further investigated by breaking down the period under study between sub-periods. By contrast, the macroeconomic variables (GDP growth and inflation rates) are found to have a significant and negative effect: the GDP growth rate negatively impacts both the liquidity coefficient (-10.94) and the solvency ratio (-0.05). This negative relationship might reflect a precautionary behaviour on the banks' part. The latter tends to expand their balance sheet and take on more risks in good times by reducing the size of their liquidity and solvency ratios, while they build up some reserves in bad times. As for the effect of the inflation rate, it is found to be insignificant on the liquidity coefficient, but significant and negative on the solvency ratio (-0.12). The relationship between the inflation rate and the solvency ratio can reflect the lower profits banks make when inflation increases. Indeed, a higher inflation rate reduces banks' profits as interest rates on (mostly) fixed rate loans are not adjusted, while funding rates move upward.

Regarding the balance sheet variables, only the relative size variable does show a significant impact on the liquidity coefficient (-281.00). In other words, when banks' relative size increases, the liquidity ratio declines. This is in line with our expectations associated with the too-big-to-fail assumption, the greater ability of large banks to diversify their funding sources and their lesser incentive to build up liquidity buffers.

Finally, the coefficient on the dummy identifying the regulatory change in 2010 regarding the tighter definition of the liquidity coefficient is found to be significant and negative in the liquidity coefficient equation, as expected. The significant and positive effect of this dummy in the solvency ratio equation might be due to the rising trend in banks' solvency ratios since the 2008/2009 financial crisis.

Overall, these results confirm some interactions between the regulatory liquidity and solvency ratios. However, the liquidity coefficient does not seem to be impacted by the aggregate financial risk variables, which comes as a surprise. In order to analyse further this latter finding, the next subsection focuses on the impact of the financial variables during periods of high stress.

Table 2.4: Simultaneous equations: Liquidity Coefficient - Solvency Ratio

	(1)	(2)
	Liquidity ratio	Solvency ratio
Liquidity ratio$_{i,t-1}$	0.625***	8.46×10^{-5} ***
	(0.005)	(2.41×10^{-5})
Solvency ratio$_{i,t-1}$	5.202***	0.891***
	(0.643)	(0.003)
Vix$_t$	-0.124	-0.000
	(1.012)	(0.005)
Interbank$_t$	-4.659	-0.064
	(13.505)	(0.062)
GDP$_t$	-10.944**	-0.050**
	(5.109)	(0.023)
Inflation$_t$	3.806	-0.119**
	(10.854)	(0.050)
Size$_{i,t-1}$	-281.002**	-0.163
	(129.351)	(0.594)
Retail$_{i,t-1}$	0.214	-0.003
	(0.710)	(0.003)
RoE$_{i,t-1}$		0.002
		(0.003)
2010 Dummy$_t$	-82.922***	0.552***
	(22.240)	(0.102)
Constant	935.021**	1.152
	(374.204)	(1.719)
Bank Fixed effects	Yes	Yes
Observations	23,264	23,264
Adjusted R-squared	0.767	0.947

Table 2.4 reports estimates of a system of 2 simultaneous equations with fixed effects. The two dependent variables are the liquidity coefficient and the solvency ratio, also used in lag among explanatory variables. The other explanatory variables include financial variables (VIX and interbank spread), macroeconomic variables (GDP and inflation rate), bank control variables (size, retail and return on equity ratio), a dummy variable (referring to 2010 as a change in definition of the liquidity coefficient, with the value 1 corresponding to the period from 2010 onwards) and individual bank fixed effects. Standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

2.4.3.1 How do financial variables impact liquidity and solvency ratios during periods of stress?

This more specific analysis allows us to determine whether our variables of interest, the financial variables, have larger effects during certain periods or not. While Table 2.4 did not show any significant effects of the financial risk variables on the regulatory ratios during the whole observation period, the objective is here to capture possible nonlinear effects whereby the impact of the financial variables on the solvency and liquidity ratios would be larger and more significant when the value of these variables exceeds certain thresholds, meaning periods of stress. To that end, we create dummy variables identifying periods of high VIX index and high interbank spreads at quarter t, named $high\_vix_t$ and $high\_interbank_t$ respectively. The $high\_vix_t$ dummy variable equals 1 when the value of the VIX index is higher than the 95th percentile of the distribution. Similarly, the $high\_interbank_t$ is a dummy variable equal to 1 when the interbank spread exceeds the 95th percentile. We also add two interaction terms to the previous specification: *(i)* an interaction term between the level of the VIX index and the dummy variable denoting high VIX period, and similarly *(ii)* an interaction term between the level of the interbank spread and the dummy variable denoting high spread periods.

The two columns of Table 2.5 show the results of this new specification. When looking at the coefficients of the interaction terms, we can see that during periods of high VIX, reflecting high risk aversion, the VIX index has a negative and (although weakly) significant impact on the liquidity coefficient (-7.33) but no significant effect on the solvency ratio. Still in contrast with our baseline findings, we also find that during periods of large interbank spread, the latter impacts the liquidity coefficient very negatively and significantly (-151.62), implying a deterioration of the bank's liquidity coefficient. These results indicate that stricter financial conditions negatively impact the liquidity coefficient in periods of stress: in those periods, banks endure the financial environment more than they steer their liquidity ratio. However, this interbank spread variable positively affects the solvency ratio during high spreads periods (1.17). This positive effect might reflect the monetary policy reaction or natural selection effects coming from competition. As regards monetary policy, interbank spread widening led central bankers to lower their policy rates during the crisis, which might have boosted banks' solvency ratios. As for competition effects, periods of very high interbank spreads might result in the failure of the weakest banks, generating a positive effect on the average solvency ratio of the more solid remaining banks. The deterioration of the interbank market sentiment has thus more negative consequences on the liquidity conditions of the bank, reflecting strong interactions between the interbank market situation and the funding bank liquidity. In turn, banks are likely to increase their level of capital buffers for precautionary motives.

This new analysis enables us to conclude that the relationship between financial variables and banks' liquidity and solvency ratios is non linear and stronger during high financial stress periods, which is in line with the literature findings on the determinants of capital ratios. This finding, combined with the fact that the new Liquidity Coverage Ratio constitutes a more stringent requirement than the former French Liquidity Coefficient, promotes a countercyclical regulation on banks' liquidity, as for solvency with the countercyclical capital buffer introduced by the Basel Committee in 2010.

Table 2.5: High stress periods

	(1)	(2)
	Liquidity ratio	Solvency ratio
Liquidity ratio$_{i,t-1}$	0.625***	8.46×10^{-5}***
	(0.005)	(2.4×10^{-5})
Solvency ratio$_{i,t-1}$	5.186***	0.891***
	(0.643)	(0.003)
Vix$_t$	0.785	-0.003
	(1.379)	(0.006)
Interbank$_t$	-14.631	-0.362***
	(22.555)	(0.104)
d_high_vix$_t$	277.724*	1.434*
	(162.366)	(0.746)
d_high_interbank$_t$	423.997**	-1.903**
	(171.167)	(0.787)
Vix$_t$ * d_high_vix$_t$	**-7.330***	**-0.025**
	(4.075)	**(0.019)**
Interbank$_t$ * d_high_interbank$_t$	**-151.619****	**1.166*****
	(75.753)	**(0.348)**
GDP$_t$	-11.442**	-0.050*
	(5.756)	(0.026)
Inflation$_t$	5.473	-0.061
	(11.205)	(0.052)
Size$_{i,t-1}$	-280.536**	-0.216
	(129.384)	(0.594)
Retail$_{i,t-1}$	0.253	-0.003
	(0.710)	(0.003)
RoE$_{i,t-1}$		0.002
		(0.003)
Constant	933.453**	1.250
	(374.598)	(1.720)
Observations	23,264	23,264
Adjusted R-squared	0.767	0.947

Table 2.5 reports estimates of a system of 2 simultaneous equations. The two dependent variables are the liquidity coefficient and the solvency ratio, also used in lag among explanatory variables. The other explanatory variables include financial variables (VIX and interbank spread), macroeconomic variables (GDP and inflation rate), bank control variables (size, retail and return on equity ratio), dummy variables (period from 2010 onwards, high VIX periods and high interbank spreads periods), interaction terms and individual bank fixed effects. Standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

2.4.3.2 How do financial risk variables impact liquidity and solvency ratios when banks are less liquid or capitalized?

The intuition we want to check now is whether the regulatory ratios of less liquid and less capitalized banks are more impacted by their financial environment. Indeed, given that these banks display smaller buffers, the regulatory minima may be more binding to them. Therefore, these banks might be facing a choice between targeting the level of their ratios or letting the external environment drive them. To that end, in Table 2.6 we introduce dummy variables identifying less liquid or less capitalised banks, on top of the previous variables used. The $d\_lessliq_{i,t-1}$ dummy variable equals 1 when the bank is below the liquidity coefficient threshold of 120%, which leaves a margin to the 100% regulatory minimum. The $d\_lesscap_{i,t-1}$ dummy variable equals 1 when the solvency ratio of the bank is below the 10% level, which is also close to the 8% regulatory minimum. The two columns of Table 2.6 include the interaction of these dummy variables $d\_lessliq$ and $d\_lesscap$ with the VIX variable and the interbank spread variable. As indicated by this table, none of these interactions is significant.[8]

Surprisingly, our latter results show that the financial variables, including global risk aversion and the interbank spread, do not have any significant impact on the regulatory ratios of banks that are less liquid or less capitalized. In this context, it is relevant to assess the effect of belonging to a larger banking group on the level of the solvency or liquidity ratios for a legal entity.

[8] A further analysis consists in introducing three kinds of interactions, to assess the impact of our financial variables on banks that are less liquid or capitalised, during the specific periods of stress, which combines the effects of the two previous specifications. However, we found that even during stress periods, the financial variables do not show any significant impact on the liquidity coefficient and the solvency ratio of banks that are less liquid or less capitalised.

Table 2.6: Less liquid/less capitalized banks

	(1)	(2)
	Liquidity ratio	Solvency ratio
Liquidity ratio$_{i,t-1}$	0.625***	8.25×10^{-5}***
	(0.005)	(2.4×10^{-5})
Solvency ratio$_{i,t-1}$	5.174***	0.890***
	(0.643)	(0.003)
Vix$_t$	0.875	-0.003
	(1.401)	(0.007)
Interbank$_t$	-12.336	-0.402***
	(22.789)	(0.106)
Vix$_t$ * d_high_vix$_t$	-7.415*	-0.024
	(4.077)	(0.019)
Interbank$_t$ * d_high_interbank$_t$	-150.454**	1.223***
	(75.803)	(0.348)
d_high_vix$_t$	280.442*	1.419*
	(162.409)	(0.746)
d_high_interbank$_t$	419.201**	-1.999**
	(171.325)	(0.787)
d_lessliq$_{i,t}$	-25.164	
	(103.024)	
d_undercap$_{i,t}$		-0.806**
		(0.329)
Vix$_t$ * d_lessliq$_{i,t}$	**-0.829**	
	(4.741)	
Vix$_t$ * d_undercap$_{i,t}$		**0.005**
		(0.014)
Interbank$_t$ * d_lessliq$_{i,t}$	**-26.567**	
	(61.211)	
Interbank$_t$ * d_undercap$_{i,t}$		**-0.007**
		(0.202)
Observations	23,264	23,264
Adjusted R-squared	0.767	0.947

Table 2.6 reports estimates of a system of 2 simultaneous equations. The two dependent variables are the liquidity coefficient and the solvency ratio, also used in lag among explanatory variables. The other explanatory variables include financial variables (VIX and interbank spread), macroeconomic variables (GDP and inflation rate), bank control variables (size, retail and return on equity ratio), dummy variables (period from 2010 onwards, least liquid banks, least capitalised banks, high vix periods and high interbank spreads periods), individual bank fixed effects and a constant. Columns (1) and (2) present estimates of the impact of financial variables on regulatory ratios for banks that are less liquid (liquidity coefficiento<120%) or less capitalised (solvency ratio<10%). Standard errors are in brackets. *** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

2.4.3.3 What is the contribution of a banking group membership?

A possible objection to our analysis is that we study the determinants of a liquidity ratio at the solo or legal entity level whereas liquidity management is usually carried out at a centralized or consolidated level within a banking group. To address this feature, in this section we include new variables to analyze the effect of belonging to a larger banking group on the level of the liquidity and solvency ratios. We thus create a dummy variable, *d_group*, to identify banks that belong to a larger group. However, the database containing this new information has only been available since the second quarter of 1997. Therefore, we start our estimations in 1997Q2 for this specific estimation, instead of starting in 1993. The first two columns of Table 2.7 show the results associated with the interaction of this dummy *d_group* with our financial risk variables, VIX and interbank spreads, in order to see if the regulatory ratios of banks belonging to a larger group are more or less sensitive to the financial risk variables. We do not find any significant effect of these interaction terms on the liquidity coefficient. However, the solvency equation shows a positive coefficient of the interaction term between the group dummy variable and the interbank spread variable (7.79). In other words, the solvency ratio of banks that belong to a larger group reacts positively to a higher interbank spread, suggesting a reaction to the financial environment at the group level. Practically, when the interbank market sentiment deteriorates, these subsidiaries benefit from a capital management at the group level.

Relatedly, in a second step, we create a dummy equal to one when the banking group displays a large excess of its liquidity coefficient (>150%) or a large excess of its solvency ratio (15%). In these cases, we assume that the sensitivity of the regulatory ratios to the financial risk variables is lower when the banking group to which the bank belongs shows an excess of liquidity or capital. Indeed, this excess of resources enables the banking group to manage liquidity or solvency centrally and to allocate support to the subsidiaries if the financial environment deteriorates. The last two columns of Table 2.7 present the results linked to this assumption. In column (3), we can see that the VIX index has a significant (at the 10% level) and negative effect on the subsidiary's liquidity coefficient when there is an excess of liquidity at the group level (-4.20). Moreover, there is no sensitivity of the subsidiary's liquidity coefficient to the interbank spread when there is excess liquidity at the group level. By contrast, in column (4), an excess of capital at the group level makes the subsidiary more sensitive in a negative way to the interbank spread (-0.86), but not to the VIX index. Said differently, the solvency ratio of banks that belong to a larger group having an excess of capital is more negatively affected by an increasing interbank spread.

Given the assumed support of the group showing an excess of capital, the subsidiary may let fluctuate its solvency ratio in response to a riskier financial environment.

These outcomes show evidence of a stronger contribution of banking group membership to the level of solvency than to the level of liquidity of its subsidiaries. While this indicates that carrying out an estimation of a liquidity coefficient at the solo level is not too problematic, we show that the reaction of the solvency ratio to the financial environment strongly depends on the management at the group level.

Table 2.7: Impact of larger banking group membership

	(1)	(2)	(3)	(4)
	Liquidity ratio	Solvency ratio	Liquidity ratio	Solvency ratio
Liquidity ratio$_{i,t-1}$	0.625***	1.255×10^{-4}***	0.624***	1.277×10^{-4}***
	(0.006)	(2.91×10^{-5})	(0.006)	(2.9×10^{-5})
Solvency ratio$_{i,t-1}$	2.569***	0.890***	2.491***	0.885***
	(0.671)	(0.003)	(0.673)	(0.003)
Vix$_t$	48.660	0.173	48.745	0.193
	(44.189)	(0.219)	(44.190)	(0.219)
Interbank$_t$	-537.877	-7.989***	-523.751	-7.978***
	(449.140)	(2.227)	(449.158)	(2.222)
Vix$_t$ * d_high_vix$_t$	-0.964	0.001	-1.554	-0.004
	(6.923)	(0.034)	(6.931)	(0.034)
Interbank$_t$ * d_high_interbank$_t$	-28.242	-0.018	-26.533	-0.021
	(71.269)	(0.353)	(71.304)	(0.353)
d_group$_i$	**854.586**	**-2.633**	816.567	-2.472
	(1,078.584)	**(5.347)**	(1,078.680)	(5.337)
Vix$_t$ * d_group$_i$	**-49.556**	**-0.188**	-48.288	-0.210
	(44.205)	**(0.219)**	(44.214)	(0.219)
Interbank$_t$ * d_group$_i$	**535.550**	**7.793*** **	515.132	8.113***
	(449.652)	**(2.229)**	(450.308)	(2.228)
d_liq_excess$_{i,t}$			**121.307*** *	
			(48.937)	
Vix$_t$ * d_liq_excess$_{i,t}$			**-4.197***	
			(2.341)	
Interbank$_t$ * d_liq_excess$_{i,t}$			**37.910**	
			(51.448)	
d_cap_excess$_{i,t}$				**0.944*** **
				(0.253)
Vix$_t$ * d_cap_excess$_{i,t}$				**0.013**
				(0.012)
Interbank$_t$ * d_cap_excess$_{i,t}$				**-0.855*** **
				(0.268)
Observations	18,114	18,114	18,114	18,114
Adjusted R-squared	0.817	0.980	0.818	0.980

Table 2.7 reports estimates of a system of 2 simultaneous equations. The two dependent variables are the liquidity coefficient and the solvency ratio, also used in lag among explanatory variables. The other explanatory variables include financial variables (VIX and interbank spread), macroeconomic variables (GDP and inflation rate), bank control variables (size, retail and return on equity ratio), dummy variables (period from 2010 onwards, high vix periods and high interbank spread periods) and individual bank fixed effects. Columns (1) and (2) present estimates including a dummy for banking group membership. Columns (3) and (4) also include dummies indicating an excess of liquidity or solvency at the banking group level. Standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

2.4.3.4 Heterogeneous effects: the effect of banks' type

The aim of the following analysis is to assess to what extent financial variables affect more the regulatory ratios of some types of banks. To this end, we interact our financial variables (VIX and interbank spread) with a dummy referring to the type of the bank. Among the six types of banks available, we focused on the three main ones: d_Com for commercial banks, d_Mut for mutual banks and d_Fin for financial firms. As with group membership, this information has only been available since 1997. Therefore, our estimations are run over the 1997q2 - 2014q4 period. Table 2.8 presents the results on our two dependent variables. Breaking down by business models uncovers interesting dynamics regarding the commercial banks' solvency ratio. We can see that the interbank spread variable has a significant and negative effect on the solvency ratios of two types of banks, commercial banks and financial firms (-1.83 and -1.28 respectively). Higher interbank spreads may reduce funding and profitability, hence retained earnings and capital of these banks, and may decrease their solvency ratio. In contrast, the VIX variable has a positive and significant impact on the solvency ratios of commercial and mutual banks (0.08 and 0.03, respectively). Higher risk aversion may induce these banks to reduce risk taking, decreasing the denominator of the solvency ratio and thus increasing the ratio. By contrast, the liquidity coefficient does not seem to be strongly affected by our financial risk variables, whatever the type of the bank. These results highlight a strong heterogeneity between the different types of banks in terms of impact of external financial variables on their levels of solvency. The solvency ratios of commercial banks seem to be the most sensitive to the external environment, due to their specific business model.

Table 2.8: Heterogeneity between banks' types

	(1)	(2)
	Liquidity ratio	Solvency ratio
Liquidity ratio$_{i,t-1}$	0.624***	1.323×10^{-4}***
	(0.006)	(2.91×10^{-5})
Solvency ratio$_{i,t-1}$	2.687***	0.888***
	(0.675)	(0.003)
Vix$_t$	0.645	-0.051***
	(2.604)	(0.013)
Interbank$_t$	-77.473	0.688**
	(56.545)	(0.280)
Vix$_t$ * d_high_vix$_t$	-1.211	-0.003
	(6.924)	(0.034)
Interbank$_t$ * d_high_interbank$_t$	-27.540	0.019
	(71.288)	(0.353)
d_fin$_i$	**114.486**	**-0.114**
	(187.415)	**(0.929)**
Vix_d_fin$_{i,t}$	**-0.124**	**-0.006**
	(4.784)	**(0.024)**
Interbank_d_fin$_{i,t}$	**37.890**	**-1.276****
	(113.938)	**(0.565)**
d_com$_i$	**185.205**	**-1.964*****
	(148.673)	**(0.738)**
Vix_d_com$_{i,t}$	**-3.407**	**0.076*****
	(3.110)	**(0.015)**
Interbank_d_com$_{i,t}$	**131.496***	**-1.830*****
	(67.173)	**(0.333)**
d_mut$_i$	**71.755**	**-0.043**
	(425.354)	**(2.108)**
Vix_d_mut$_{i,t}$	**-0.646**	**0.032****
	(3.177)	**(0.016)**
Interbank_d_mut$_{i,t}$	**74.496**	**-0.423**
	(70.704)	**(0.353)**
Observations	18,114	18,114
Adjusted R-squared	0.790	0.953

Table 2.8 reports estimates of a system of 2 simultaneous equations. The two dependent variables are the liquidity coefficient and the solvency ratio, also used in lag among explanatory variables. The other explanatory variables include financial variables (VIX and interbank spread), macroeconomic variables (GDP and inflation rate), bank control variables (size, retail and return on equity ratio), dummy variables (period from 2010 onwards, high vix periods, high interbank spread periods and types of bank), individual bank fixed effects and a constant. Columns (1) and (2) present estimates of the interaction between financial variables and regulatory ratios depending on the type of bank (commercial, mutual banks or financial firms). Standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

2.4.3.5 Disentangling the numerator and the denominator of the liquidity coefficient

To determine whether the impacts of financial variables on the regulatory ratios are predominant on the asset or the liability side of banks, this section disentangles the liquidity coefficient between liquid assets (the numerator of the liquidity coefficient) and the net cash outflows (denominator). To normalize the numerator and the denominator of the liquidity coefficient taken separately, we calculate the share of these two variables in the bank's total assets. We keep the solvency ratio as our third dependent variable. We thus run a system of simultaneous equations now including 3 equations whose dependent variables are liquid assets, net cash outflows, and the solvency ratio, respectively.

This new estimation (Table 2.9) indicates that among our aggregate financial risk variables, the most notable significant effect we capture is the impact of the interbank spread on the denominator of the liquidity coefficient, namely the share of net cash outflows, in high stress times (0.92). While the impact of the interbank spread variable on the net cash outflows is negative on the whole period (-0.32), it becomes positive during periods of large spreads, reflecting high stress. This means that when the interbank spread exceeds the 95th percentile of its distribution, a rise in the spread brings about a larger share of net cash outflows. This in turn entails a deterioration of the bank's liquidity ratio. This effect might reflect the mechanism whereby long-term debt markets shut down for banks during periods of high spreads, compelling them to increase the share of their short-term funding.

Regarding interactions within the liquidity ratio or the solvency ratio, Table 2.9 provides results similar to the previous tables. In the first two columns, the numerator and the denominator of the liquidity coefficient display positive interactions: higher cash outflows lead to more liquid assets (0.20), which is expected with regard to the requirement for banks to display a liquidity coefficient higher than 1. More surprisingly, a larger share of liquid assets leads to larger cash outflows (0.004), to a lesser extent. More liquid assets lead banks to meet higher outflows in the next period. Moreover, while the solvency ratio has a positive impact on the share of liquid assets (0.11), its effect is found to be negative on the share of cash outflows (-0.01), which is expected as higher solvency means a more stable funding structure.

As for the solvency ratio (column 3), neither the share of liquid assets nor the share of cash outflows are found to have a significant impact on the ratio, confirming that the relationship between liquidity and solvency seems to be only a one-way relationship.

These new results confirm the strong interactions occurring between the share of liquid assets, cash outflows, and the solvency ratio, which is in line with our previous findings. At the same time, they show that the effect of the financial variables in periods of stress on the liquidity coefficient mostly materialises on the liability side, through net cash outflows, in line with Duijm and Wierts (2016).

All these results allow a better understanding of the channels of liquidity stress transmission. The effect is only visible in periods of very high stress and is channelled mostly through unstable liabilities.

Table 2.9: Simultaneous equations: Liquid assets - Cash outflows - Solvency Ratio

	(1)	(2)	(3)
	Liquid assets	Cash outflows	Solvency ratio
Liquid assets$_{i,t-1}$	0.577***	0.004**	0.003
	(0.006)	(0.002)	(0.002)
Cash outflows$_{i,t-1}$	0.200***	0.794***	0.004
	(0.014)	(0.004)	(0.005)
Solvency ratio$_{i,t-1}$	0.110***	-0.010***	0.892***
	(0.008)	(0.002)	(0.003)
Vix$_t$	-0.010	-0.000	-0.003
	(0.017)	(0.005)	(0.006)
Interbank$_t$	-0.795***	-0.319***	-0.351***
	(0.285)	(0.084)	(0.104)
Vix$_t$ * d_high_vix$_t$	0.005	0.011	-0.026
	(0.051)	(0.015)	(0.019)
Interbank$_t$ * d_high_interbank$_t$	0.874	0.920***	1.168***
	(0.957)	(0.281)	(0.348)
GDP$_t$	-0.250***	0.037*	-0.051*
	(0.073)	(0.021)	(0.026)
Inflation$_t$	0.078	0.121***	-0.061
	(0.142)	(0.042)	(0.052)
Size$_{i,t-1}$	-0.386	0.670	-0.209
	(1.634)	(0.480)	(0.594)
Retail$_{i,t-1}$	-0.080***	-0.011***	-0.002
	(0.009)	(0.003)	(0.003)
RoE$_{i,t-1}$			0.002
			(0.003)
Observations	23,264	23,264	23,264
Adjusted R-squared	0.833	0.906	0.947

Table 2.9 reports estimates of a system of 3 simultaneous equations. The three dependent variables are the numerator of the liquidity coefficient (Liquid assets), the denominator of the liquidity coefficient (Cash outflows), both normalized, and the solvency ratio, also used in lag among explanatory variables. The other explanatory variables include financial variables (VIX and interbank spread), macroeconomic variables (GDP and inflation rate), bank control variables (size, retail and return on equity ratio), dummy variables (period from 2010 onwards, high vix periods and high interbank spreads periods), individual bank fixed effects and a constant. Standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Sources: ACPR, INSEE and Bloomberg - Authors' calculations.

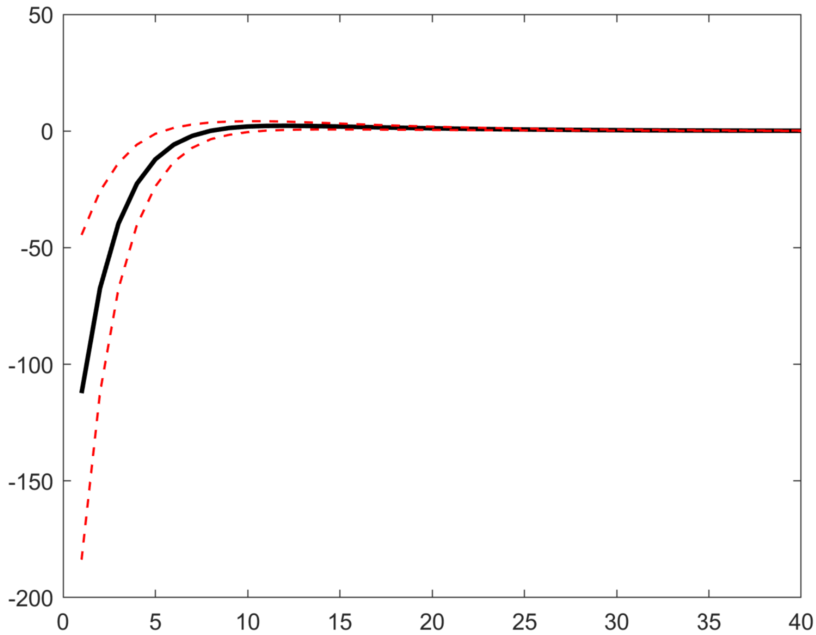
2.5 Supervisory liquidity stress-test

As discussed so far, liquidity shocks can deteriorate banking liquidity and solvency. It could thus be interesting to assess the response of liquidity to market liquidity shocks. The aim is to see the extent to which banks recover their initial level of solvency and liquidity after going through a crisis. To this aim, we study the Impulse Response Functions (IRFs) that can be derived from the previous equations.

Indeed, we can notice that the model in Table 2.4 is actually an Exogenous VAR model (or X-VAR(1) model), due to the presence of exogenous variables. Such a model can therefore be inverted, yielding IRFs, or responses of the endogenous variables to a shock to exogenous variables (the aggregate financial risk variables). Therefore, we compute the IRFs to shocks on the interbank spread variable (jumping to 400bp) and the VIX variable (increasing to 80 points) and look at the impact on the liquidity coefficient and the solvency ratio, using the model displayed in Table 2.4. We consider successively the impacts of *(i)* a shock to interbank spreads in crisis times (measured by the high spread period) on the liquidity coefficient (see Figure 2.1) and on the solvency ratio (see Figure 2.2) and *(ii)* a shock to the VIX in crisis times (measured by the high VIX period) on the liquidity coefficient (see Figure 2.3) and on the solvency ratio (see Figure 2.4). In all figures, the 90 percent confidence bands are based on Monte Carlo simulations. They are drawn around the median IRF.

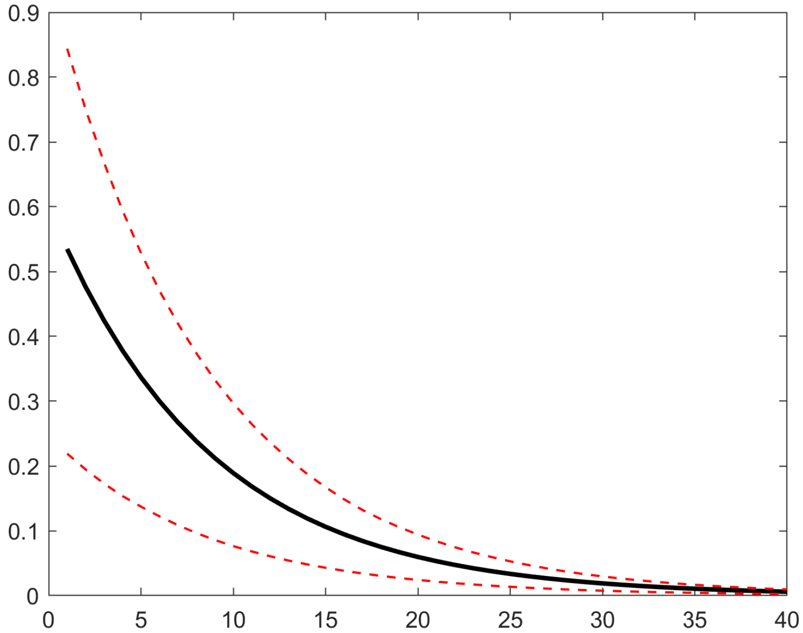
It is worth noting that the effects of the shocks to the solvency ratio are much longer-lived than the effects on the liquidity coefficient, with a vanishing of the effect (i.e. when the confidence interval end up crossing the x-axis) on the liquidity coefficient between 5 and 10 quarters, as compared to more than 20 quarters for the solvency ratio. Therefore the latter seems to be more persistent, in line with its higher autoregressive coefficient in our simultaneous equations. While the market liquidity shock jeopardizes much more the liquidity position of banks in the short run in magnitude, the lesser impact of the shock on solvency takes a long time to fade away, which can also be damaging for the solidity of the bank. This last stress test illustrates our conclusions on the negative impact of market liquidity shocks on banks' solvency and liquidity.

Figure 2.1: Impulse Response Function: shock to interbank spread on Liquidity Coefficient



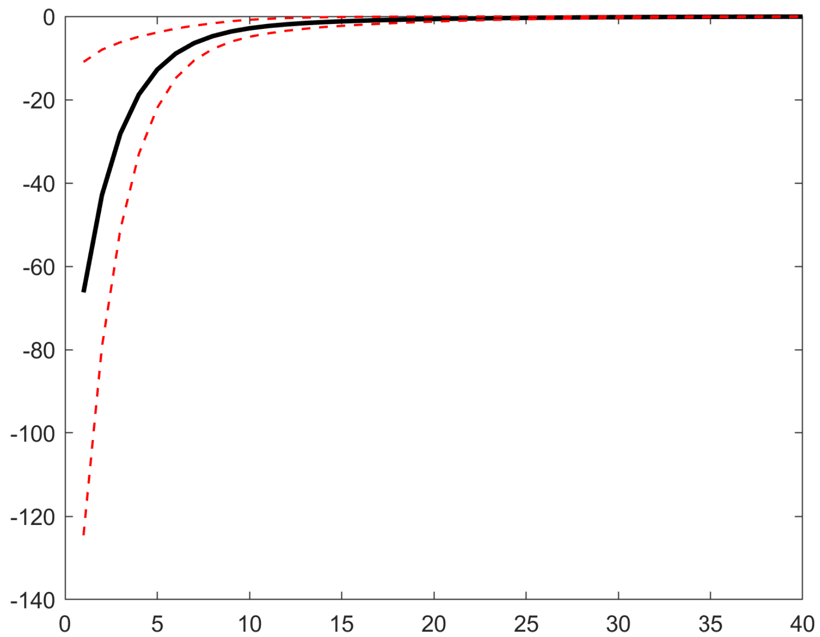
Note: the figure displays the response of the liquidity ratio (in percentage point wrt baseline) to a shock on the interbank spread by 70bp, on the basis of the inversion of the equation in Table 2.6.
Sources: ACPR, Authors' calculations.

Figure 2.2: Impulse Response Function: shock to interbank spread on Solvency Ratio



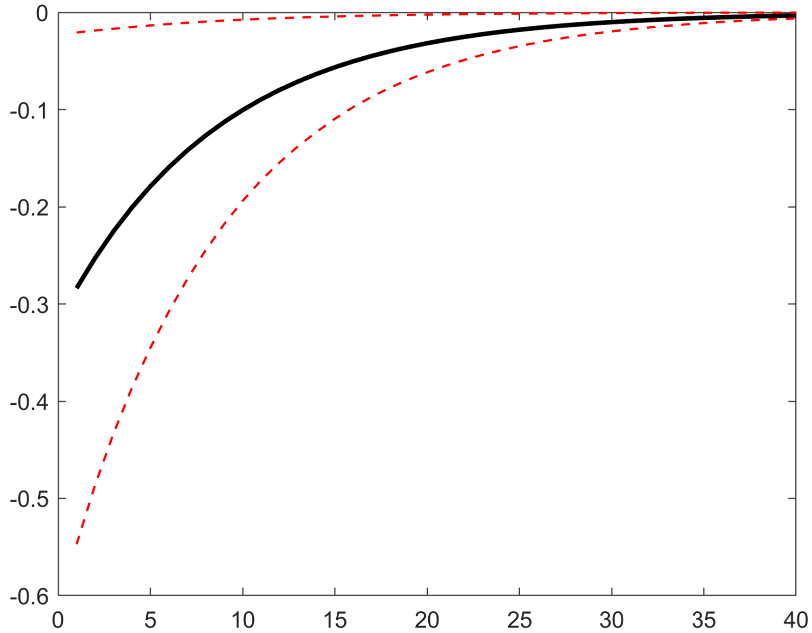
Note: the figure displays the response of the Solvency ratio (in percentage point wrt baseline) to a shock on the interbank spread by 70bp on the basis of the inversion of the equation in Table 2.6.
Sources: ACPR, Authors' calculations.

Figure 2.3: Impulse Response Function: shock to VIX on Liquidity Coefficient



Note: the figure displays the response of the liquidity ratio (in percentage point wrt baseline) to a shock to the VIX by 10 points on the basis of the inversion of the equation in Table 2.6.
Source: ACPR, Authors' calculations.

Figure 2.4: Impulse Response Function: shock to VIX on Solvency Ratio



Note: this figure displays the response of the solvency ratio (in percentage point wrt baseline) to a shock to the VIX by 10 points on the basis of the inversion of the equation in Table 2.6.
Sources: ACPR, Authors' calculations.

2.6 Conclusion

This study aimed at estimating the determinants of banks' liquidity ratios, taking into account the interactions between solvency and liquidity as well as between market liquidity and funding liquidity risks. Indeed, our results show that a higher level of solvency enables the liquidity ratio to improve. By contrast, we do not find evidence that solvency ratios are affected the banks' liquidity. Likewise, financial risk variables affect liquidity and solvency ratios only during periods of high stress, with a larger adverse effect on liquidity than solvency, confirming the evidence of strong interactions between market liquidity and bank funding liquidity during crisis periods. The financial risk channel is found to materialize mostly on the liability side, through net cash outflows. Finally, the impact of the banking group membership affects the relationship between financial risk variables and the solvency ratio, but we failed to find evidence of liquidity management at the group level. Likewise, we find that financial firms and commercial banks are more affected by the financial risk variables on the solvency side than on the liquidity side.

Our empirical results show that liquidity may fluctuate quite significantly when the market environment is more adverse. In the case of France, liquidity coefficient may largely drop in crisis times as a consequence of cash outflows. This behaviour is in line with the first Hypothesis of our theoretical model, according to which banks adjust their liquidity coefficient down in crisis times. It is also consistent with Goodhart's advice to adjust the requirements when needed, particularly in periods of uncertainty. In these circumstances, the implementation of a liquidity regulation in a contracyclical form, encouraging accumulation of liquidity in good times and using it in bad times, seems to be more appropriate to prevent future crises. Le Liquidity Coverage Ratio was initially designed in this way but is also seen as an indicator of the financial health of banking institutions. Despite the recommendations provided by supervisory authorities on its use, the reduction of this liquidity buffer is considered as a negative signal reflecting a lack of liquidity resources, which is rapidly punished by either rating agencies or markets and investors. It is thus necessary to remind the aim of this liquidity regulation, namely the availability of liquidity reserves that can be used when needed.

* * *

Chapter 3

Credit lines: a concentrated risk more than a run risk?

* * *

Most papers address the banks' liquidity risk related to credit lines as a potential run, similar to deposits run, that occurs in periods of uncertainty. Nevertheless, credit lines, and more problematically drawdowns, display several features endangering banks's liquidity management. We highlight the inability for banks to fulfill their loan commitments with their repayments, with a very low correlation between these two components. We emphasize the high concentration in credit lines and drawdowns, which prevents/hinders banks from using portfolio diversification to address arising drawdowns. Finally, we show that this concentration generates high volatility in banks' drawdowns, coming from a limited number of firms. In this context, banks could then experience substantial liquidity problems themselves. We thus show the need to rethink the usual question regarding credit lines as a massive behaviour that could endanger banks' liquidity position. The concentrated and unfunded characteristics of loan commitments make banks in a liquidity trap at any time of the cycle.

* * *

This Chapter is an adaptation of a collaboration with Paul Beaumont, Mathias Lé and Thibault Libert.

3.1 Introduction

Banks' liquidity risk related to credit lines is usually addressed as a potential run, similar to deposits run, which may arise in periods of uncertainty. A line of credit is an agreement between a bank (lender) and a firm (borrower), upon request, allowing the latter to draw funds at any time, up to a fixed limit, at a given rate, and for a specified period of time. In particular, Lins et al. (2010) show the importance of credit lines as a precautionary instrument, guaranteeing that arising future growth opportunities can be funded even if external capital is difficult to obtain. Accordingly, on the one hand, banks must provide funds to those firms that meet a liquidity need. On the other hand, banks fund these credit lines by means of other sources of liquidity coming from firms that do not draw on credit lines at the same time. Provided that banks can comply with the drawdowns of credit lines, this liquidity management ensures an efficient allocation of liquidity over the different users at the aggregated level of the economy. However, when conditions deteriorate and firms experience liquidity issues or lose confidence in liquidity availability in the future, they may draw on their credit lines simultaneously. In this case, this efficient allocation of liquidity does not longer hold and can jeopardize the banks' liquidity position. Demiroglu and James (2011) show that despite the prediction that firms should mainly use banks' lines of credit for their future liquidity needs, public firms still hold significant amounts of cash, by fear of being unable to obtain the committed credit from banks.

In this chapter, we show that this liquidity issue faced by banks is likely to arise at any time of the cycle, even during expansion periods. Indeed, credit lines, and more problematically drawdowns, display the following features, endangering banks' liquidity management. First, we highlight the inability for banks to fulfill their loan commitments with their repayments, with a very low correlation between these two components. Second, we emphasize the high concentration in credit lines and drawdowns, which prevents banks from using portfolio diversification to address drawdowns. Third, we show that this concentration generates high volatility in banks' drawdowns, coming from a limited number of firms. In this context, banks could thus experience substantial liquidity problems themselves. Consequently, we claim the need to rethink the usual question regarding credit lines such as a massive behaviour that could endanger banks' liquidity positions. The concentrated, volatile and unfunded characteristics of loan commitments imply banks can fall into a liquidity trap at any time of the cycle.

Our findings on liquidity risks arising from loan commitments belong to the specific literature on credit lines. In the aftermath of the Great Financial Crisis, many papers (Campello et al. (2011), Campello et al. (2012) among others) aimed at analyzing these liquidity instruments, their role and their impacts during periods of uncertainty. Indeed, Acharya et al. (2013) argue that banks may not be able to comply with the commitments of credit lines for all firms in the economy at all times. In the case of a liquidity stress on the whole corporate sector, banks will be unable to provide liquidity to this sector because the total committed facilities will sharply exceed the available funds coming from the remaining healthy firms.

Within this literature on credit lines, the liquidity risk is thus usually considered as a run, similarly to deposits run. Kashyap et al. (2002) indicate that banks specializing in deposits activity also seem to specialize in credit lines, so that the two activities can share the costs of liquidity provisions. In this case, risk can be managed as long as deposit withdrawals and commitment takedowns are not too highly correlated. In this regard, Ivashina and Scharfstein (2010) and Ippolito et al. (2016) show that simultaneous runs emerged during the crisis. Firms decided to draw on their credit lines at the same time to address their liquidity issues or because of uncertainty regarding liquidity availability. In order to deal with this well-known risk, banks can manage the risk of double runs through selective granting of credit lines. Sufi (2009) and Nikolov et al. (2019) indicate that access to credit lines is a good indicator of financial constraints. Due to the liquidity risk, credit lines are mainly granted to large firms or firms with high level of cash. Additionally, Acharya et al. (2014) describe the positive effects of credit lines revocations after a negative firms' profitability shock and promote the use of credit lines covenants. They particularly emphasize the relationship between liquidity risks and liquidity management, associated with credit lines.

However, Gatev and Strahan (2006) provide evidence that when liquidity dries up and borrowers draw on their commercial paper backup lines, banks experience deposits inflows, probably because of government guarantees and safety nets. Acharya and Mora (2015) also explain that in periods of stress, government interventions guarantee that banks have no difficulty to provide the growing credit demand, even though banks experience significant and simultaneous drawdowns. Campello et al. (2012) confirm that credit lines did not dry up during the crisis and provided liquidity that European firms needed to invest and cope with the contraction. In these circumstances, it appears that the risk supported by banks is not necessarily the risk of run, *i.e.* an aggregated liquidity shock involving many firms at the same time.

This brings us to the first contribution of this chapter. While prior research focused on the aggregate risk of credit lines, we consider a new source of liquidity risk related to credit lines. Specifically, the important concentration displayed by credit lines among banks' portfolios can endanger their liquidity position. That is, if one firm holding most of the credit lines of a bank faces a liquidity shortage and suddenly decides to draw on the whole committed loan, the bank may find difficult to deliver on its commitment. Relatedly, Jiménez et al. (2009) document that firms with a higher expected default probability are more likely to use credit lines. Norden and Weber (2010) also find that credit lines exhibit abnormal patterns approximately 12 months before default. These features confirm the relevance of idiosyncratic risk in the management of credit lines among banks' portfolios. This article is the first, to our knowledge, to address the idiosyncratic risk related to credit lines that can jeopardize banks' liquidity positions at any time of the cycle, outside crisis periods.

This article also contributes to the literature on liquidity risks related to unused and used banks' credit lines. Our chapter brings to light the materialization of the risk through the occurrence of drawdowns. While most of the papers study the potential risk arising from yet-to-be-drawn credit lines, we assess and analyze these drawdowns, reflecting the actual risk faced by banks. More precisely, their high concentration, their large volatility as well as banks' inability to fully fund drawdowns make them very vulnerable to liquidity shocks arising suddenly from a small number of drawing firms. These idiosyncratic features of drawdowns constitute a new finding among the literature on credit lines.

The third contribution of this chapter relates to the challenges of defining and quantifying drawdowns of credit lines. Unused credit lines are easily observable, as off-balance sheet component. However, when created, drawdowns are mixed up with other traditional loans, making them difficult to disentangle. This article is thus the first, to our knowledge, to provide a methodology that separately identifies drawdowns. This identification is applicable to any national credit register and enables a powerful extension of all studies on unused credit lines by analyzing the *actual* liquidity risk that drawdowns constitute instead of *potential* risks linked to unused credit lines.

The remainder of the chapter is structured as follows. Section 3.2 presents the data we use and explains the identification strategy for credit lines, drawdowns and repayments. In Section 3.3, we describe general and specific features of the different components related to loan commitments. In Section 3.4, we indicate the next steps of the paper that we will implement empirically. The final section concludes.

3.2 Data

3.2.1 The French credit register

We use a comprehensive dataset on bank-firm level credit from the French national credit register, maintained by the Banque de France (*"Centrale des risques"*), over the period 2006 - 2016. This register reports all the credits granted by any resident institution providing credit. The population of borrowers/debtors includes any resident and nonresident legal entity (firms, local governments and administrations) as well as any natural person having a professional activity operating nationwide. Institutions established in France have to report any credit exposure to a given firm as soon as the total outstanding exposure on this firm exceeds €25,000. The credit register also provides information related to firms. Size, location and 5-digits sector are indicated for all firms. Likewise, when firms have a turnover above €0.75 million or a total outstanding amount higher than €380K, the Banque de France estimates internally its own credit ratings for a large population of resident firms (about 300,000) and in particular for small firms that are generally not under the scope of the private rating agencies. The Banque de France has been recognized as an external credit assessment institution (ECAI) for its company rating activity.

The credit register allows us to disentangle the quarterly information according to the type of credit granted among 12 distinct types of loans belonging to 6 broad categories (see Appendix 3.A), including undrawn credit lines. Our final sample consists of 679 credit institutions (we further refer to these institutions as "banks" for simplicity purpose). The number of banks decreases over time, from 602 in 2006Q1 to 409 in 2016Q4, reflecting the growing concentration of the banking market. Conversely, the total number of firms is 970,102, with an increasing population over the period, from 415,072 in 2006Q1 to 605,104 firms in 2016Q4.

3.2.2 Identification of credit lines drawdowns

An important contribution of this paper relates to the challenging identification of credit lines drawdowns. Most of national credit registers document loan commitments (unused) and granted loans. This last category includes traditional loans as well as credit lines drawdowns, without specifying which part of these granted loans comes from credit lines. Analyzing the unused credit lines is a first and useful insight on the liquidity risk on which banks are exposed. As a second step, it will be even more powerful to study the realization of this risk, by analyzing the drawdown of credit lines. To do that, we implement a methodology that enables us to identify the drawdown at every period for every bank-firm credit line.

In the credit register, when a company draws on its line of credit, the stock of loan commitments decreases while the stock of granted credit increases. More precisely, the stock of granted credit of one or several types of credit grows in the exact opposite proportion to the decline in the stock of credit line. We use this temporal matching in the variations of the stock of granted credit/credit line to identify drawdowns. In general, we identify a drawdown as follows:

$$Drawdown_{b,f,t} = \begin{cases} -\Delta CreditLine_{b,f,t} > 0 & \text{if } 0.99 \leq \frac{-\Delta CreditLine_{b,f,t}}{\Delta GrantedCredit_{b,f,t}} \leq 1.01 \\ 0 & \text{otherwise} \end{cases} \tag{3.2.1}$$

We thus measure the amount of drawdown as the opposite of the negative variation of the credit line stock ($\Delta CreditLine_{b,f,t}$), only when it matches the positive amount of variation of granted credit ($\Delta GrantedCredit_{b,f,t}$), within a 1% confidence interval.

A further interesting component is credit line *repayments*. Firms may as well recapitalize their lines of credit in order to keep available liquidity and draw on in the future. Defined as the reciprocal of credit line *drawdown*, the amount of *repayment* is defined as the positive variation of the credit line stock ($\Delta CreditLine_{b,f,t}$), only when it matches the negative amount of variation of granted credit ($\Delta GrantedCredit_{b,f,t}$), within a 1% confidence interval. Specifically, overdraft facilities generate a succession of drawdowns and repayments. This component can also be important in the banks' liquidity management, as we will display further in the paper. Indeed, one way for banks to manage their liquidity situation regarding credit lines is to use the repayments coming from some firms to provide the simultaneous drawdowns of other firms.

$$Repayment_{b,f,t} = \begin{cases} \Delta CreditLine_{b,f,t} > 0 & \text{if } 0.99 \leq \frac{\Delta CreditLine_{b,f,t}}{-\Delta GrantedCredit_{b,f,t}} \leq 1.01 \\ 0 & \text{otherwise} \end{cases} \tag{3.2.2}$$

For the sake of convenience, we define *drawdown* and *repayments* always as positive amounts. These different components (credit lines, drawdowns and repayments) are important tools used by banks and firms to manage their liquidity. Their assessment thus provides interesting insights on the risks related to loan commitments.

3.2.3 Limits to this identification and robustness tests

This methodology of identification of drawdowns is made possible by the concomitance between positive flows of new credit and negative flows of credit line. However, we can quickly observe some drawbacks that we need to address as far as possible. We briefly summarize these aspects of our measurement of drawdowns here and provide some robustness tests to deal with these issues.

In particular, this methodology leads us to miss a part of the drawdowns. When a firm draws on its credit line and simultaneously asks for an extension (or closure) of its remaining credit line, the final variation of the credit line will not match any variation in granted credit. Likewise, if the firm is granted a new traditional credit simultaneously to a drawdown, the total amount of credit granted will not match with the negative flow of credit lines. In these examples, we will not observe the actual drawdowns. To mitigate these matching issues, we compare the variations of credit lines and granted credit, according to each type of credit available in the credit register (see Appendix 3.A), individually, as well as any combination (sum) of several types of credit matching with the variation of the credit line.

Similarly, this methodology may lead us to identify as drawdowns some flows that are not drawdowns but traditional credit. In the specific case of a cancelation of a credit line and a simultaneous traditional credit of the same amount granted by the bank to the firm, we will wrongly consider the variation as a drawdown. Given that these missing points come from "coincidences", we can reasonably assume that they represent a very small part of the drawdowns. The best way we found to address this issue is to use the most restrictive confidence interval (1%), in order to capture the most accurate drawdowns.

Finally, to be sure to capture a consistent amount of drawdowns, we run some robustness checks. We replicate the main results of the paper using different definitions of drawdowns, with confidence intervals at the 5% and at the 10%. Figures 3.B.1, Figure 3.B.2, Figure 3.B.3, Figure 3.B.4 and Figure 3.B.5, as well as Table 3.B.1 of Appendix 3.B show that results are robust to more or less restrictive identification thresholds and that the patterns observed are reliable.

3.3 Descriptive statistics

3.3.1 Main variables

We first display descriptive statistics regarding our main variables of interest, granted loans, undrawns credit lines, drawdowns and repayments. Table 3.1 reports the number of observations, the mean, the standard deviation, the minimun and maximun of these variables. We can observe that the average amount of credit lines (€216,000) is almost half of the average amount of granted loans (€530,000). This shows that bank-firm relationships use this instrument to a large extent. Regarding the use of credit lines, the average amount of drawdowns is around €7,000 per quarter per bank-firm relationship, while the average amount of repayment is only €4,000 per quarter. This indicates a gap between credit lines drawdowns and repayments, that banks have to offset to stay liquid. The difference in the number of observations for granted credit/credit lines (39.6 million) and drawdowns/repayments (38.9 million) comes from the first period for which we cannot obtain the amount of these last variables due to the specific computation based on variation with lagged values.

Table 3.1: Descriptive statistics : granted credit, credit lines, drawdowns and repayments

Variables	Number of observations	Mean	Standard Deviation	Minimum	Maximum
Granted loans	39,576,055	529.5633	7199.588	0	6873851
Undrawn credit lines	39,576,055	216.0803	6190.663	0	3902667
Drawdowns	38,870,894	7.272143	437.4579	0	428125
Repayments	38,870,894	4.942733	370.8118	0	650970

Table 3.1 reports descriptive statistics for the main variables analysed in this paper at the quarter level, over the period 2006Q1 to 2016Q4. Amounts of granted loans, undrawn credit lines, drawdowns and repayments are expressed in thousand €.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

3.3.2 Aggregate evolution

Descriptive statistics enables us to highlight some key patterns of our variables of interest. Figure 3.1 plots the aggregate amount of credit lines for each quarter, contrasted with the aggregate amount of granted credit over the period. The chart clearly describes a gradually increasing evolution of the total amount of granted credit over the 2006-2016 period. Conversely, the aggregate amount of credit lines fluctuates around €200 billion over the whole period. Credit lines steadily increase from 2006 to 2011, then decrease until 2014 to cross below the average €200 billion. At the end of the period, credit lines recover slightly just below this average threshold. These patterns display the differences in the use of traditional credit and credit lines, according to the business cycle. We can assume a more attractive use of credit lines, such a liquidity instrument for firms during periods of uncertainty or crisis, in order to keep access to financing if conditions deteriorate. On the opposite, the very stable and gradually rise in credit granted reflects the same path of production growth and the number of borrowing firms.

Figure 3.1: Evolution of aggregate granted credit and credit lines

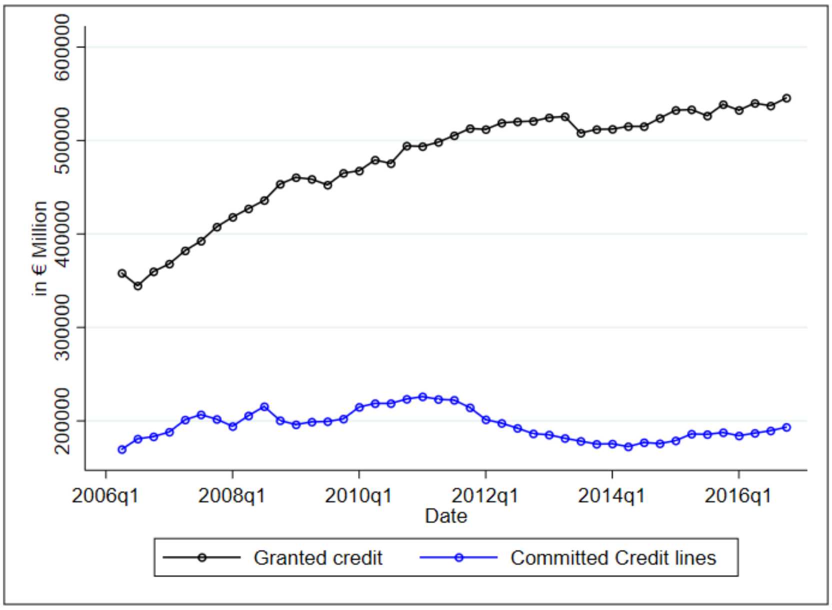


Figure 3.1 displays the time series of aggregate granted credit and credit lines over the 2006Q1-2016Q4 period.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

Figure 3.2 plots two graphs dealing with the aggregate amount of drawdowns (in red) and repayments (in green) for each period. Overall, we observe cyclical trends for both variables. Regarding drawdowns, a dip often occurs on the third quarter of each year, followed by a peak on the fourth quarter, which could reflect seasonal treasury needs of firms, related to their activity. As for repayments, it is difficult to establish a seasonal pattern, but a cyclical trend is clearly pronounced. We can assume that firms draw on their credit lines when they need and rebuild them when they are able over the year. This is the first outcome that questions the ability of banks to manage the liquidity risk related to drawdowns with repayments.

Figure 3.2: Evolution of aggregate drawdowns and repayments

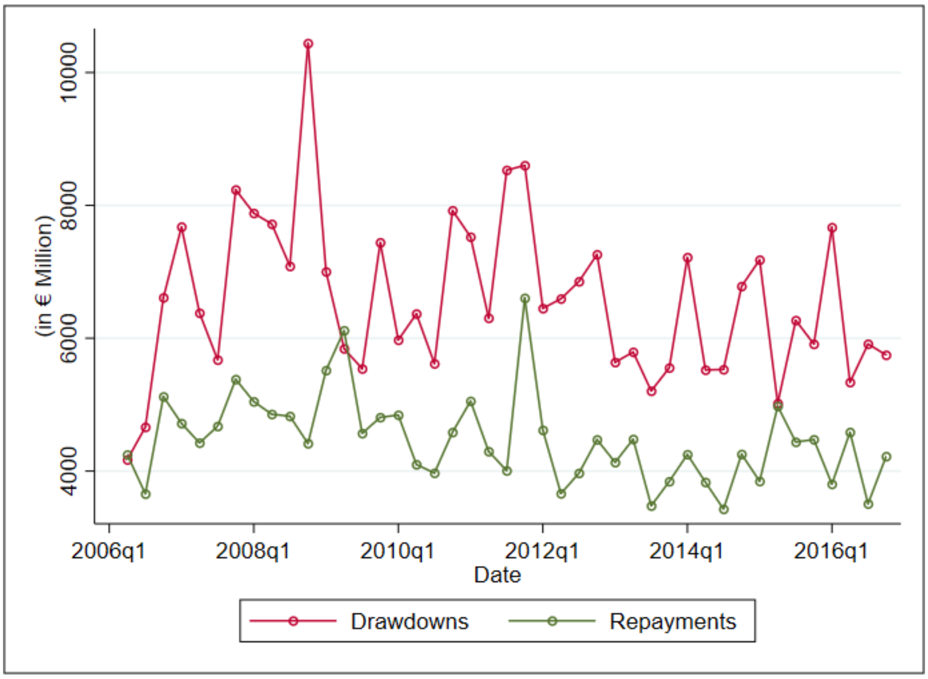


Figure 3.2 displays the time series of aggregate drawdowns and repayments over the 2006Q1-2016Q4 period.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

Moreover, we can observe a larger amount of drawdowns over the whole period, continuously above the amount of repayments. Drawdowns fluctuate mainly between €6 and €8 billion, while repayments rather range between €4 or €5 billion at each period. This gap in the two magnitudes of drawdowns and repayments compromises the banks' capacity of using the repayments of a given firm to provide the drawdowns of an other firm. If banks can deal it by this way in a small extent, they are not able to offset the total amount of drawdowns occurring at each period. Furthermore, drawdowns are then considered as loans and generate additional required bank capital. Consequently, liquidity problems can even turn to solvency problems. As far as the aggregate level is concerned, these differences in the overall patterns and in the magnitudes of the aggregate amounts of drawdowns and repayments confirm the inability of banks to manage their drawdowns with their repayments.

An other interesting picture is that we observe 3 important peaks among the drawdowns. The total amount of this variable exceeds €10 billion in 2008Q4, and €8 billion in 2007Q4 and 2011Q3-Q4. Regarding the fourth quarter of 2007 and 2008, we can reasonably assume larger needs of firms during the global financial crisis. The large drawdowns in 2011 put some questions unresolved at the moment, that will deserve assessment in the next steps of the paper. Similarly, we observe 2 peaks among the repayments. The total amount of repayments exceeds €4 billion two times : in 2009Q2 and 2011Q4. We can assume that the 2009 peak follows the previous drawdown related to the global financial crisis, reflecting firms trying to rebuild their credit lines. The 2011 peak coincides with the drawdown peak, for which we do not have explanation yet.

These huge drawdowns observed can provide interesting results, given their magnitude. In a further step of this paper, it would be interesting to analyse the consequences of such enormous drawdowns by focusing on the supply of credit of the banks concerned. We thus would like to analyse of the ability to originate new loans or credit lines after a liquidity shock such as these sudden huge drawdowns.

3.3.3 Correlation

Given the observed patterns of drawdowns and repayments at the aggregate level, a more precise assessment of the correlation between aggregate drawdowns and repayments will confirm or infirm the previous presumptions. At the aggregate level, the correlation between drawdowns and repayments is 0.64. This is a positive and quite large correlation, indicating that at each period, drawdowns and repayments evolve in the same direction, positively or negatively. However, this correlation is quite far from 1, which means that drawdowns and repayments do not totally evolve perfectly together. That is why we observed these differences between the two patterns in Figure 3.2. This confirms the only partial ability for banks to offset the drawdowns of credit lines with the repayments of credit lines. At the wide economy level, credit lines may constitute a liquidity risk.

To further extend this correlation analysis, we now turn to the correlation at the bank level. Indeed, even if at the aggregate level of the economy, drawdowns are partially compensated by repayments, it is also important for each bank, at their individual level, to offset these drawdowns, in order to respect their commitments while staying resilient. To do that, we now compute the correlation for each bank. The average of all these bank level correlations only reaches 0.14, which is still positive but quite weak and much lower than the correlation at the aggregate level (0.64). This new result indicates that at their individual level, banks are almost totally unable to offset their drawdowns with their repayments, because they do not evolve in the same direction at each quarter. This lack of correlation creates a need for liquidity management, and maybe a liquidity risk, for banks. Specifically, Table 3.2 displays a large dispersion in these correlations according to banks. While only 10% of banks show a correlation above 0.5, 25% of them indicate a negative correlation equal or lower than -0.06. This last figure indicates that for 1 quarter of banks, when they have to face more drawdowns, they also have to face less repayments, whereas they need it more at this moment. We can imagine that the extreme case is the story occurring during crises, when all companies draw on their credit lines simultaneously and almost no company rebuild its credit lines at this moment. In our context, we can see that this behaviour is identified on the whole period 2006-2016, said differently, some banks are unable to provide their due drawdowns with their repayments available. This issue constitutes an off-balance sheet liquidity risk for vulnerable banks that face important drawdowns.

Table 3.2: Correlations between drawdowns and repayments

Variables	Observations	Mean	SD	p10	p25	p50	p75	p90
At the aggregate level	44	0,64	0,00	0,64	0,64	0,64	0,64	0,64
At the individual bank level	12370	0,14	0,26	-0,11	-0,06	0,08	0,33	0,50

Table 3.2 reports estimates of correlations between drawdowns and repayments, at the aggregated level and at the individual bank level, over the 2006Q2-2016Q4 period.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

3.3.4 Concentration

3.3.4.1 A highly concentrated distribution

We turn in this section to the concentration of credit lines and drawdowns. We found that credit lines, and particularly drawdowns represent a liquidity risk for individual banks that cannot offset their drawdowns with their repayments. We now want to analyze the concentration of credit lines and drawdowns in order to measure the magnitude of the potential and actual risk when it occurs.

We first display the concentration of credit lines, reflecting a potential additional liquidity risk. As a reminder, credit lines constitute only undrawn loan commitments, thus not materialized loans yet but a good indicator of the risk faced by banks. To do that, Figure 3.3 describes the cumulative distribution of credit lines, with undrawn commitments ordered by percentile according to their size: the four graphs describe the share in the total amount of credit lines of (i) top 1%, (ii) top 5%, (iii) top 10% and (iv) top 20% of the largest credit lines borrowers for each quarter. As shown in Figure 3.3,the distribution of credit lines is very concentrated. Indeed, the top 1% largest credit lines represent more than 85% of the total amount of credit lines. More importantly, the top 5% largest credit lines borrowers concentrate around 95% of credit lines. This very high degree of concentration highlights that banks do not diversify their portfolios regarding credit lines borrowers, which may represent an important liquidity risk.

Figure 3.3: Cumulative distribution of credit lines

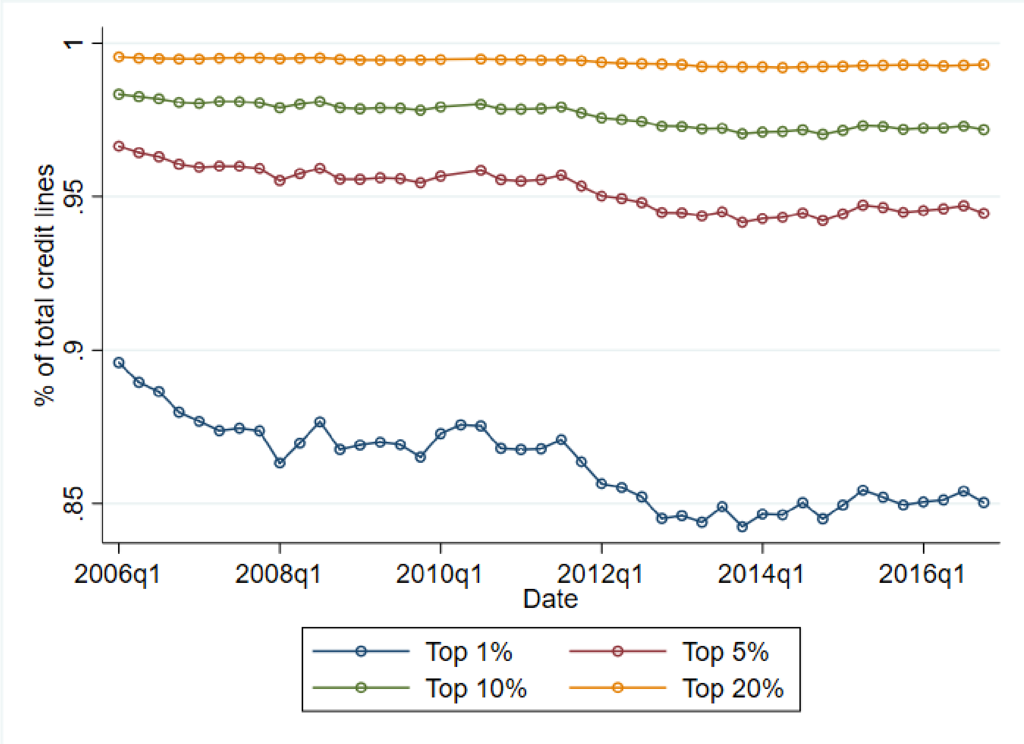


Figure 3.3 displays the cumulative distribution of credit lines over the 2006Q1-2016Q4 period. The top 1% (respectivement 5%, 10% and 20%) corresponds to the share of credit lines held by the 99th (respectivement 95th, 90th and 80th) percentile of the firm distribution among the total amount of credit lines.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

Then, Figure 3.4 displays the similar distribution for drawdowns. In contrast with credit lines, for which risk is only possible, drawdowns represent the risk already occurred, meaning that firms drew on their credit lines. In this case, we can observe the actual risk that banks faced in the past. The distribution of drawdowns is less concentrated than credit lines, but still very concentrated. The top 1% largest drawdowns represent between 50% and 70% of the total amount of drawdowns, depending on the quarter, while the top 10% largest drawdowns concentrate around 90% of drawdowns. The almost total amount of drawdowns is thus done by a very small number of firms.

Figure 3.4: Cumulative distribution of drawdowns

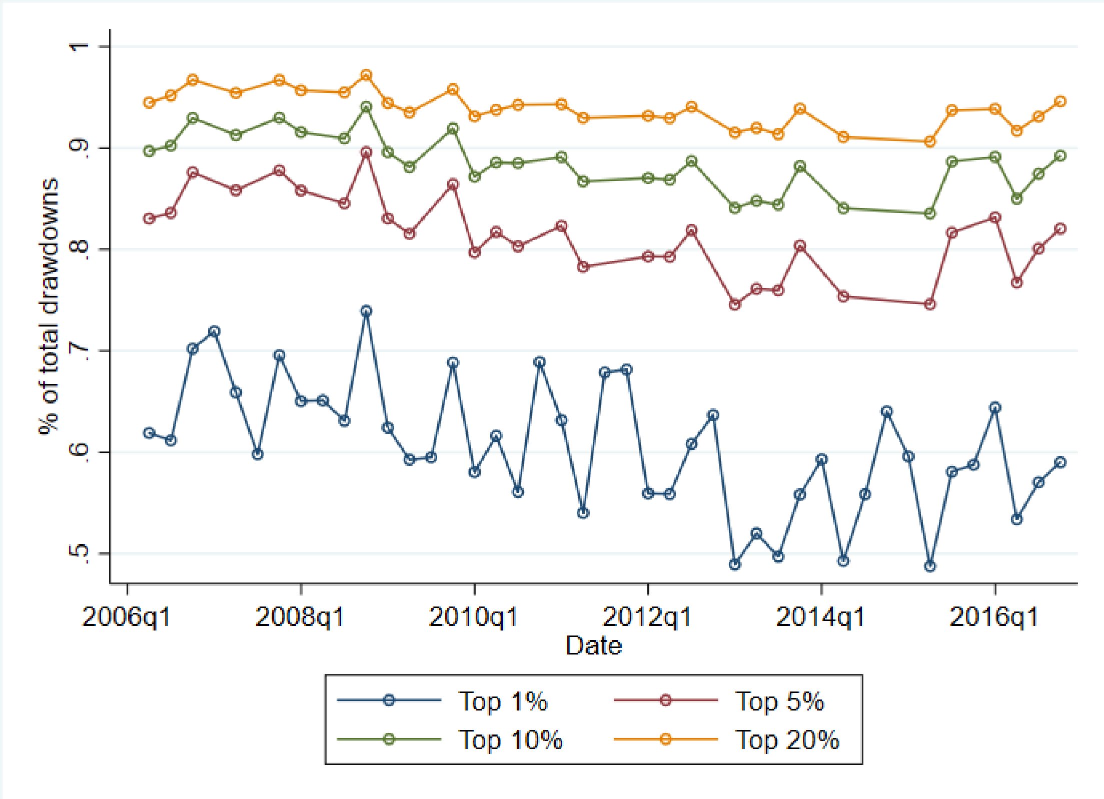


Figure 3.4 displays the cumulative distribution of drawdowns, on quarterly data, over the 2006Q1-2016Q4 period. The top 1% (respectivement 5%, 10% and 20%) corresponds to the share of drawdowns held by the 99th (respectivement 95th, 90th and 80th) percentile of the firm distribution among the total amount of drawdowns.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

Many studies analyzing credit lines address the issue related to these commitments such as the risk of a run on all credit lines drawdowns simultaneously, similarly to runs in deposits. However, we show that the risk related to credit lines or drawdowns rather comes from a very small number of credit lines borrowers that concentrate the majority of loan commitments. If one or several of these main borrowers decide to take down the total of their whole credit lines, it can suddenly jeopardize the liquidity position of the related banks. This liquidity risk related to credit lines does not require firms running on their banks for drawdowns at the same time and can arise at any time, outside crisis or uncertainty periods.

3.3.4.2 An amplified volatility

In order to verify to what extent a small number of credit lines borrowers could destabilize banks' liquidity position, we now plot the relationship between the concentration of credit lines and the volatility of drawdowns. We expect that the more concentrated are the loan commitments, the more volatile are the drawdowns, due to the lack of diversification. Figure 3.5 indicates a very positive relationship between banks' concentration and their drawdowns' volatility. Banks with the highest concentration of credit lines, meaning the least diversified portfolio of loan commitments, also have the highest volatility in their drawdowns. This can be explained by the lower ability for banks to offset these firms' drawdown shocks.

Figure 3.5: Concentration of credit lines and volatility of drawdowns

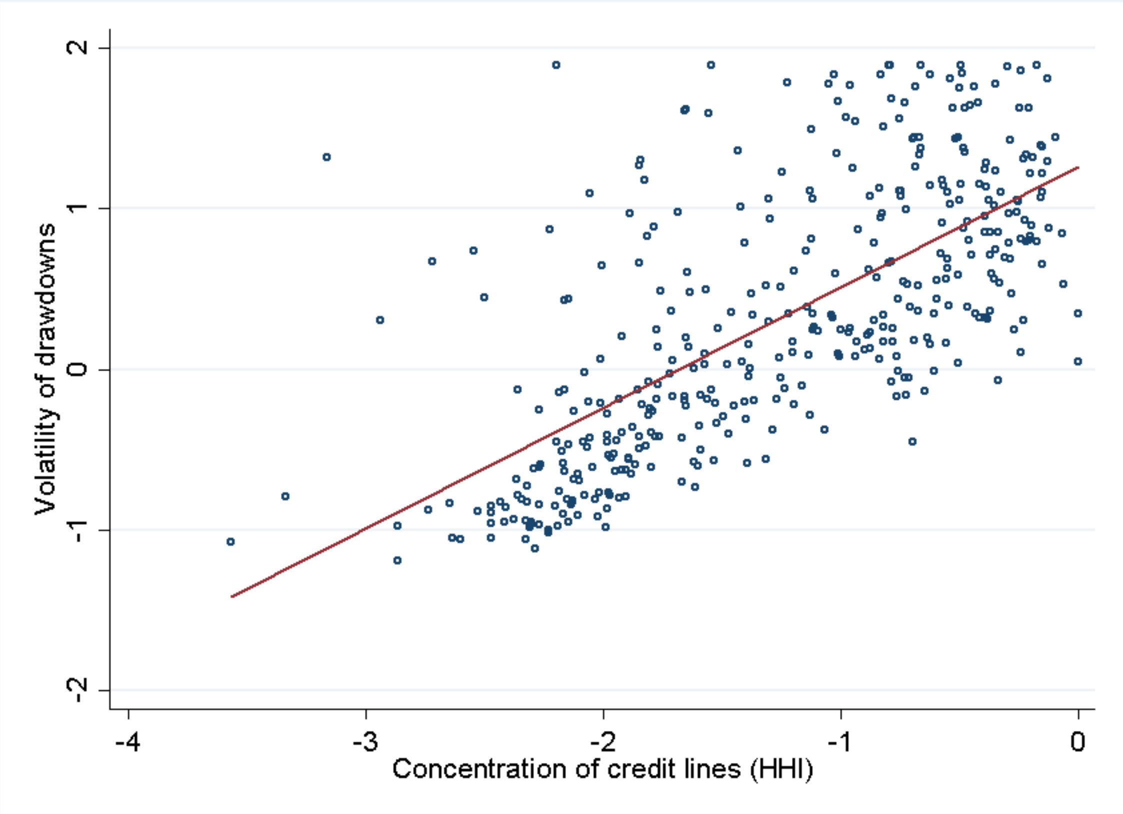


Figure 3.5 displays the relationships between the concentration of credit lines and the volatility of drawdowns, on quarterly data, over the 2006Q1-2016Q4 period. The concentration of credit lines is computed as the average Herfindahl Hirschmann Index of banks' credit lines portfolio, taken in logarithm. The volatility of drawdowns is the standard deviation of the variable, taken in logarithm.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

3.4 Empirical Strategy

Let us now briefly describe the empirical estimations we aim at implementing in a future, extended version of the present paper. Following the first insights of concentration in credit lines, we aim at verifying empirically the importance of the idiosyncratic risk related to these lines. To do that, we will apply to credit lines the Beaumont et al. (2019)'s methodology. In their paper, they dissociate the growth rate of long-term credit into a bank component, a firm component and a macro-component. Similarly, we wish to decompose the total drawdowns at the bank level into a common component for all borrowers of the same bank ("bank component") and a component specific to each of the different borrowers ("firm component"). In the case of total drawdowns at the level of a bank that are mainly determined by the bank component, then we can consider the drawdown risk as rather aggregated. However, if it is rather determined by the firm components, the risk is idiosyncratic.

3.4.1 Methodology

As detailed in section 3.2, the identification of drawdowns enables us to write them as follows:

$$\begin{aligned} D_{b,f,t} &= -\Delta CL_{b,f,t} \\ &= \frac{-\Delta CL_{b,f,t}}{2} \cdot 2 \cdot \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{b,f,t} + CL_{b,f,t-1})} \\ &= \underbrace{\frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2}}_{\omega_{b,f,t}} \cdot \underbrace{2 \cdot \frac{-\Delta CL_{b,f,t}}{(CL_{b,f,t} + CL_{b,f,t-1})}}_{\Delta^{MPGR} CL_{b,f,t}} \end{aligned} \tag{3.4.1}$$

where $D_{b,f,t}$ and $CL_{b,f,t}$ respectively refer to the drawdown and the outstanding amount of credit line of the firm f to the bank b at the quarter t.

We can see the expression of a "mid-point growth rate" (MPGR) in the right-hand side of the equation $\Delta^{MPGR} CL_{b,f,t} = 2 \cdot \frac{-\Delta CL_{b,f,t}}{(CL_{b,f,t}+CL_{b,f,t-1})}$ that Beaumont et al. (2019) use for their decomposition of long-term credit. Similarly, this mid-point growth rate of credit line complies with the characteristics required so that this decomposition methodology will apply perfectly on drawdowns.

In particular, we put the following aggregation properties at the firm, bank and aggregated levels :

- For each firm $f \in F$:

$$D_{f,t} = -\Delta CL_{f,t} = -\sum_B \Delta CL_{b,f,t} = \sum_B D_{b,f,t}$$

- For each bank $b \in B$:

$$D_{b,t} = -\Delta CL_{b,t} = -\sum_F \Delta CL_{b,f,t} = \sum_F D_{b,f,t}$$

- At the aggregated level of the economy :

$$D_t = -\Delta CL_t = -\sum_B \sum_F \Delta CL_{b,f,t} = \sum_B \sum_F D_{b,f,t}$$

These aggregation properties also hold with the MPGR, $\Delta^{MPGR} CL_{b,f,t}$

- For each firm $f \in F$:

$$\begin{aligned}
\Delta^{MPGR} CL_{f,t} &= 2 \cdot \frac{\Delta CL_{f,t}}{(CL_{f,t} + CL_{f,t-1})} \\
&= 2 \cdot \frac{\sum_B \Delta CL_{b,f,t}}{(CL_{f,t} + CL_{f,t-1})} \\
&= \sum_B 2 \frac{\Delta CL_{b,f,t}}{(CL_{f,t} + CL_{f,t-1})} \\
&= \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{f,t} + CL_{f,t-1})} \cdot 2 \cdot \frac{\Delta CL_{b,f,t}}{(CL_{b,f,t} + CL_{b,f,t-1})} \\
&= \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{f,t} + CL_{f,t-1})} \cdot \Delta^{MPGR} CL_{b,f,t}
\end{aligned}$$

- For each bank $b \in B$:

$$\begin{aligned}
\Delta^{MPGR} CL_{b,t} &= 2 \cdot \frac{\Delta CL_{b,t}}{(CL_{b,t} + CL_{b,t-1})} \\
&= \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{b,t} + CL_{b,t-1})} \cdot \Delta^{MPGR} CL_{b,f,t}
\end{aligned}$$

- At the aggregated level of the economy :

$$\begin{aligned}
\Delta^{MPGR} CL_t &= 2 \cdot \frac{\Delta CL_t}{(CL_t + CL_{t-1})} \\
&= \sum_F \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_t + CL_{t-1})} \cdot \Delta^{MPGR} CL_{b,f,t}
\end{aligned}$$

We then propose to adapt Beaumont et al. (2019)'s methodology to this equation term $\Delta^{MPGR}CL_{b,f,t}$:

$$\Delta^{MPGR}CL_{b,f,t} \equiv 2 \cdot \frac{-\Delta CL_{b,f,t}}{(CL_{b,f,t} + CL_{b,f,t-1})} = \alpha_{f,t} + \beta_{b,t} + \epsilon_{b,f,t}$$

with $\alpha_{f,t}$ and $\beta_{b,t}$ respectively refering to the firm and bank fixed effects.

By this way, when we estimate drawdowns (equation (3.4.1)) with weighted least squares (WLS), by specifying the weight as $\left\{\omega_{b,f,t} = \frac{(CL_{b,f,t}+CL_{b,f,t-1})}{2}\right\}$, we find the estimated parameters $\left\{\hat{\alpha}^{WLS}_{f,t}\right\}$ and $\left\{\hat{\beta}^{WLS}_{b,t}\right\}$, that enables us to reconstitute $\left\{\Delta^{MPGR}CL_{f,t}\right\}$ and $\left\{\Delta^{MPGR}CL_{b,t}\right\}$ (see Appendix 3.C for more details). Finally, the estimated parameters $\left\{\hat{\alpha}^{WLS}_{f,t}\right\}$ and $\left\{\hat{\beta}^{WLS}_{b,t}\right\}$ imply :

- For each firm $f \in F$:

$$\Delta^{MPGR}CL_{f,t} = \frac{-\Delta CL_{f,t}}{(CL_{f,t} + CL_{f,t-1})} = \hat{\alpha}^{WLS}_{f,t} + \sum_{B} \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{f,t} + CL_{f,t-1})} \cdot \hat{\beta}^{WLS}_{b,t}$$

- For each bank $b \in B$:

$$\Delta^{MPGR}CL_{b,t} = \frac{-\Delta CL_{b,t}}{(CL_{b,t} + CL_{b,t-1})} = \hat{\beta}^{WLS}_{b,t} + \sum_{F} \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{b,t} + CL_{b,t-1})} \cdot \hat{\alpha}^{WLS}_{f,t}$$

These empirical decompositions indicate that the WLS estimation of the *Haltiwanger* growth rate of drawdowns of the firm f enables us to decompose the total of the firm f's credit lines expressed such as the firm's fixed effect plus the sum of the fixed effects specific to its lending banks b weighted by the importance of credit lines between f and b within all f's credit lines.
Symmetrically, the WLS estimation of the *Haltiwanger* growth rate of drawdowns of the bank b enables us to decompose the total of credit lines of the bank b expressed such as the bank's fixed effect plus the sum of the fixed effects specific to the borrowing firms f of b weighted by the importance of credit lines between b and f within all b's credit lines.

Consequently, we will be able to highlight the importance of the bank and firm components within the credit lines portfolio of banks. In the case of an important firm component, we can assume that the risk associated with credit lines is rather idiosyncratic than aggregated.

3.4.2 Normalisation

To make this methodology the most appropriate, the $Drawdown_{b,f,t}$ variable requires to be normalised. As it stands, a large firm will have larger drawdowns than smaller firms. Given that we want to observe the risk on banks' side, an amount of drawdowns in billion will not have the same consequences for the bank according to what it represents within the bank's portfolio. To address this issue, we analyze how to normalise our variable of interest in order to find the aggregation properties that still allow for our decomposition methodology.

We thus examine the following estimation : $\tilde{D}_{b,f,t} = \frac{D_{b,f,t}}{CL_{b,f,t-1}} = \alpha_{f,t} + \beta_{b,t} + \epsilon_{b,f,t}$ and find the relevant weights that will allow us to run this estimation and establish our decomposition.

We finally find the following expressions reflecting that the weight $\omega_{b,f,t} = CL_{b,f,t-1}$ is appropriate in order to decompose the normalized drawdowns at the bank, firm, and aggregated levels between a bank component and a firm component (see Appendix 3.D for more details) :

$$\begin{cases} \tilde{D}_{b,t} = \sum_F \frac{CL_{b,f,t-1}}{CL_{b,t-1}} \cdot \hat{\alpha}_{f,t} + \hat{\beta}_{b,t} \\ \tilde{D}_{f,t} = \hat{\alpha}_{f,t} + \sum_B \frac{CL_{b,f,t-1}}{CL_{f,t-1}} \cdot \hat{\beta}_{b,t} \end{cases}$$

These expressions allow us to decompose normalized drawdowns at different levels of aggregation as a linear combination of firm and bank fixed effects estimated by WLS. We will thus be able to decompose these aggregate normalized drawdowns at the bank level as the sum of a bank component and a firm component to examine the fraction that can be attributed to idiosyncratic and aggregated shocks. The implementation of this afore described methodologoly is left for the future, extended version of the present paper.

3.5 Conclusion

Banks' liquidity risk related to credit lines is usually addressed as a potential run that arises in periods of uncertainty. When conditions deteriorate and firms experience liquidity issues or lose confidence in liquidity availability in the future, they draw on their credit lines simultaneously, which in turn jeopardizes the banks' liquidity position. In this chapter, we show that this liquidity issue that banks address is likely to arise at any time of the cycle, even during expansion periods. Indeed, credit lines and drawdowns can sharply endanger banks' liquidity management. First, we highlight the inability for banks to fulfill their loan commitments with their repayments, with a very low correlation between these two components. Second, we emphasize the high concentration in credit lines and drawdowns, which prevents banks from using portfolio diversification to address arising drawdowns. Finally, we show that this concentration generates high volatility in banks' drawdowns, coming from a limited number of firms. In this context, banks could then experience substantial liquidity problems themselves. Consequently, we emphasize the need to rethink the usual question regarding credit lines such as a massive behaviour that could endanger banks' liquidity positions. The concentrated, volatil and unfunded characteristics of loan commitments imply banks can fall into a liquidity trap at any time of the cycle.

Appendices of Chapter 3

3.A French national credit register: breakdown by loan type

- Short-term loans (i.e. with an initial maturity shorter than 1 year)
  - Overdrafts on ordinary account
  - Accounts receivable financing
  - Factoring
  - Other short-term loans
- Medium and Long-term loans (i.e. with an initial maturity longer than 1 year)
  - Export credits
  - Other medium and long-term loans
- Financial Leases and Leasing
  - Equipment leases
  - Property leases
- Securitized loans
- Undrawn credit lines
  - Undrawn loans
  - Opening of documentary credit
- Guarantees commitments

3.B Robustness tests: results with identifications of drawdowns at the 5% and 10% confidence intervals

Figure 3.B.1: Evolution of aggregate drawdowns defined at the 1%, 5% and 10% confidence intervals

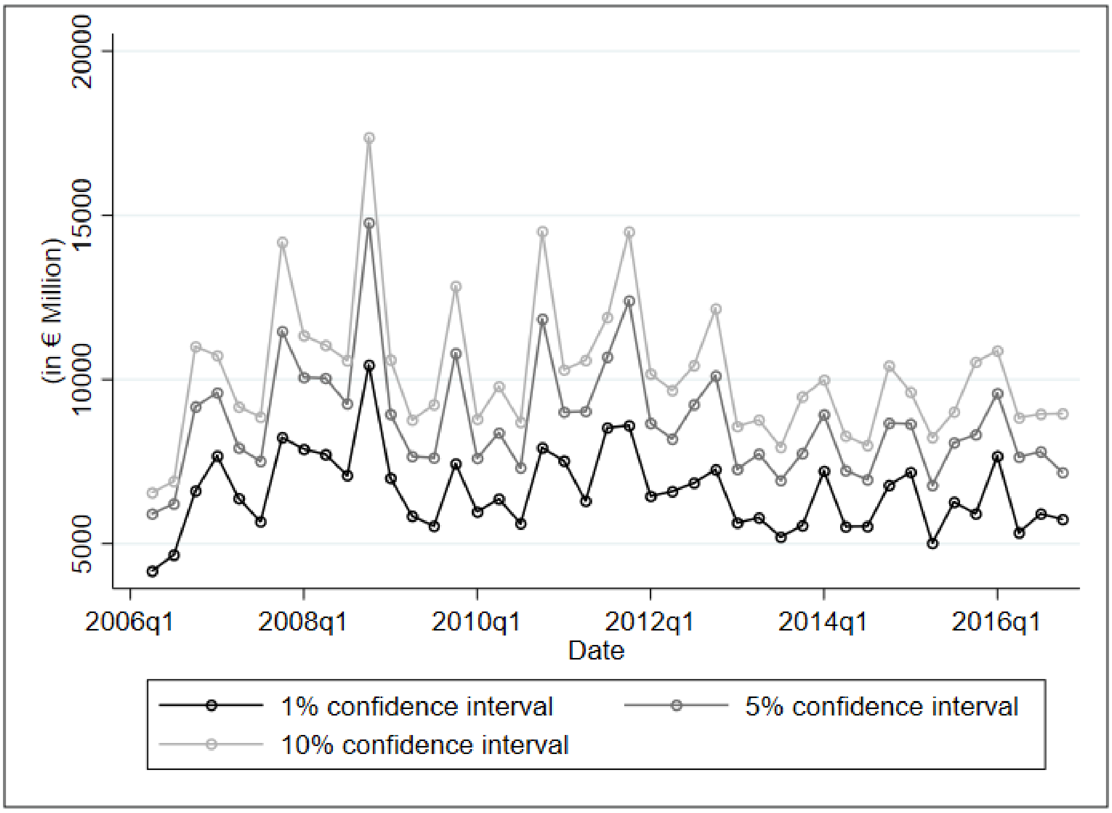


Figure 3.B.1 displays the time series of aggregate drawdowns, defined at the 1%, 5% and 10% confidence intervals, over the 2006Q1-2016Q4 period.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

Table 3.B.1: Correlations between drawdowns and repayments

Variables	Correlations	Obs	Mean	SD	p10	p25	p50	p75	p90
Defined at the 1% confidence level	Aggregate level	44	0,64	0,00	0,64	0,64	0,64	0,64	0,64
	Bank level	12370	0,14	0,26	-0,11	-0,06	0,08	0,33	0,50
Defined at the 5% confidence level	Aggregate level	44	0,68	0,00	0,68	0,68	0,68	0,68	0,68
	Bank level	12932	0,14	0,26	-0,12	-0,06	0,08	0,32	0,50
Defined at the 10% confidence level	Aggregate level	44	0,64	0,00	0,64	0,64	0,64	0,64	0,64
	Bank level	13129	0,13	0,26	-0,12	-0,06	0,05	0,31	0,50

Table 3.B.1 reports estimates of correlations between drawdowns and repayments at the aggregated level and at the individual bank level, over the 2006Q2-2016Q4 period. Drawdowns and repayments are defined at the 1%, 5% and 10% confidence intervals.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

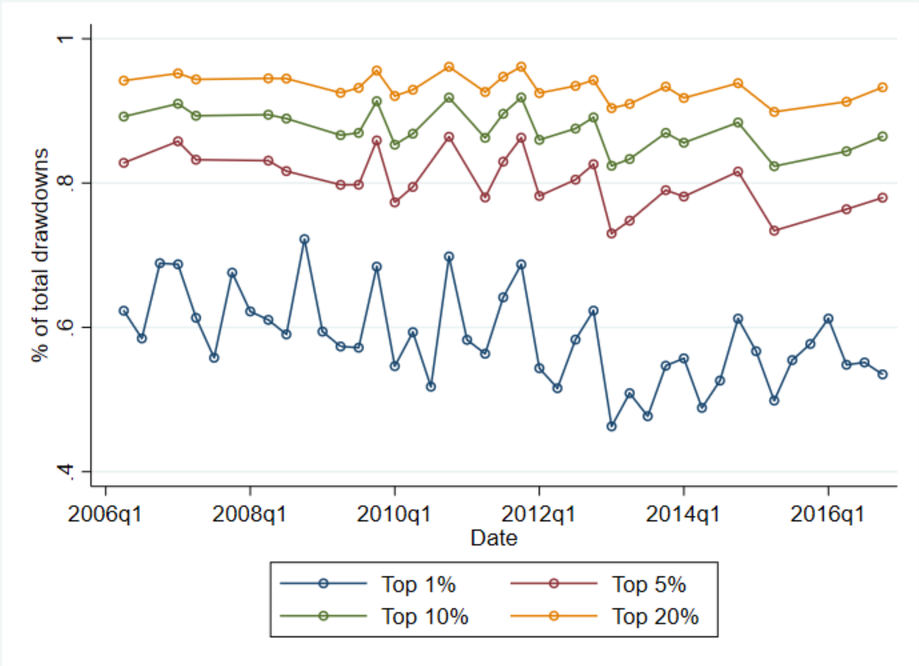


Figure 3.B.2: 5% confidence interval

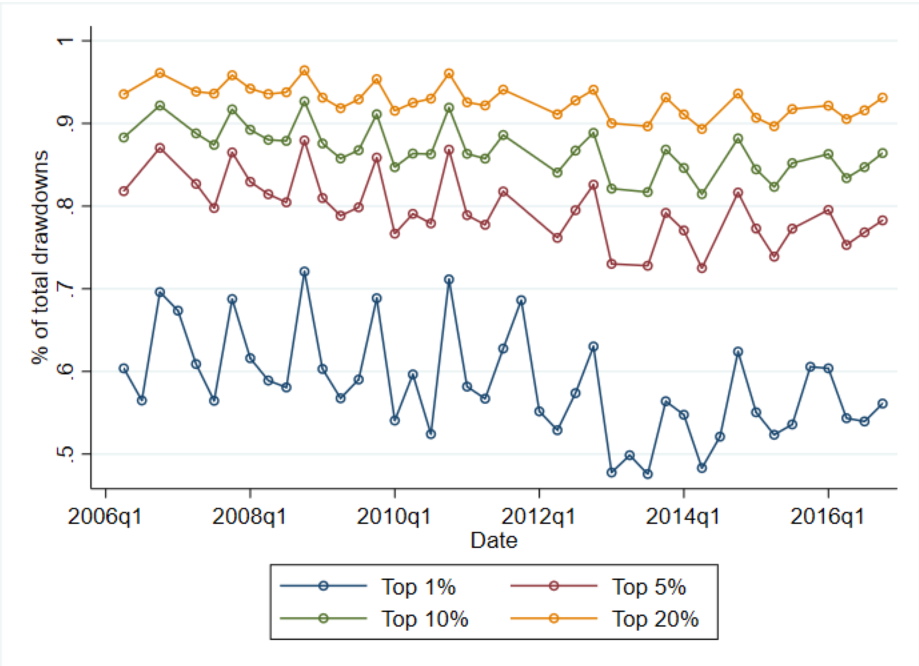


Figure 3.B.3: 10% confidence interval

Figures 3.B.2 and 3.B.3 display the cumulative distributions of drawdowns, defined at the 5% confidence interval (top plot) and at the 10% confidence interval (bottom plot), on quarterly data, over the 2006Q1-2016Q4 period. The top 1% (respectivement 5%, 10% and 20%) corresponds to the share of drawdowns held by the 99th (respectivement 95th, 90th and 80th) percentile of the firm distribution among the total amount of drawdowns.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

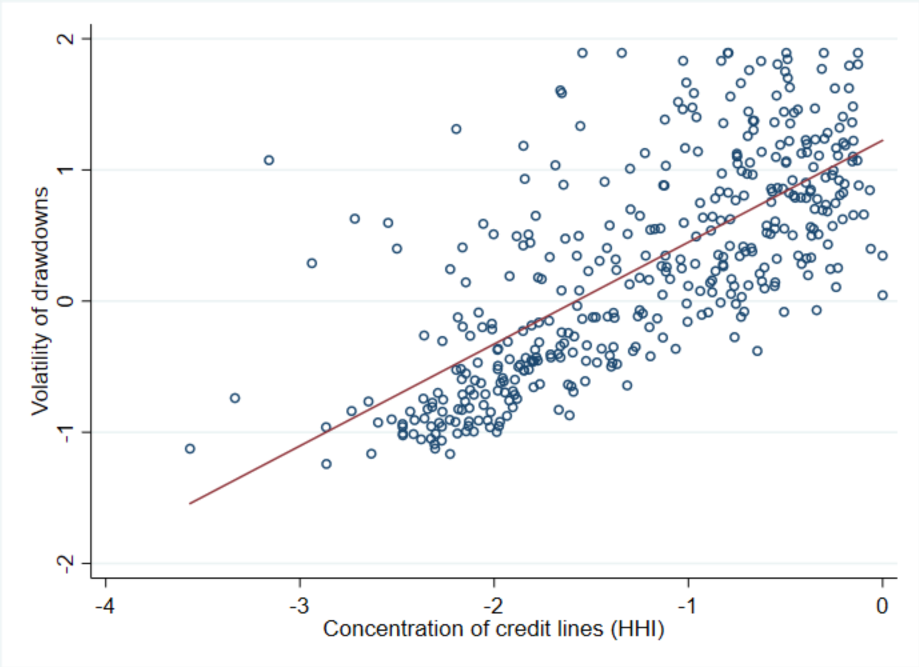


Figure 3.B.4: 5% confidence interval

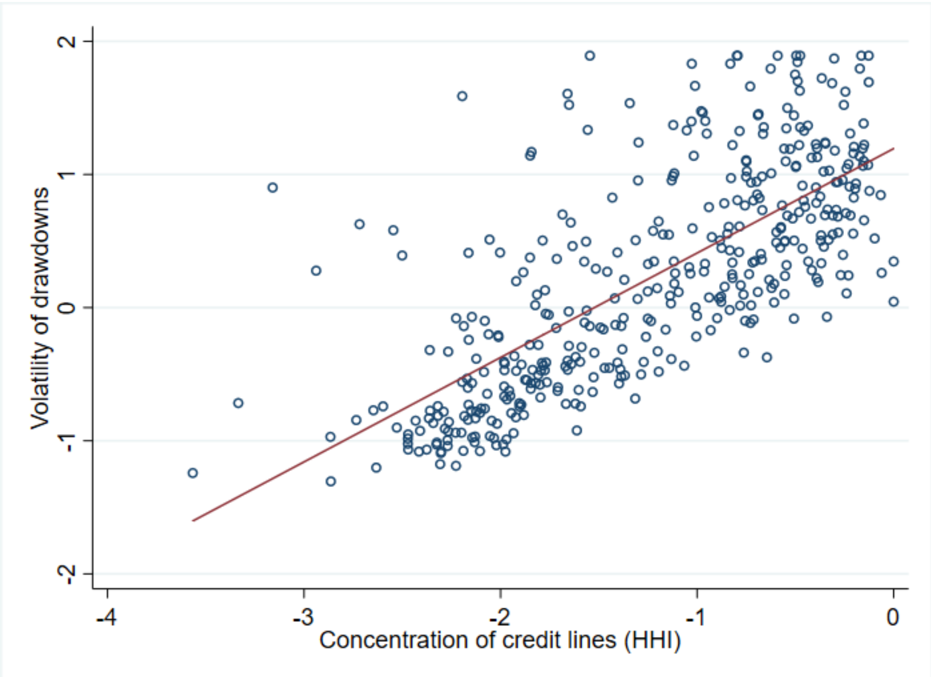


Figure 3.B.5: 10% confidence interval

Figures 3.B.4 and 3.B.5 display the relationships between the concentration of credit lines and the volatility of drawdowns, defined at the 5% confidence interval (top plot) and at the 10% confidence interval (bottom plot), on quarterly data, over the 2006Q1-2016Q4 period. The concentration of credit lines is computed as the average Herfindahl Hirschmann Index of banks' credit lines portfolio, taken in logarithm. The volatility of drawdowns is the standard deviation of the variable, taken in logarithm.
Sources: Banque de France - ACPR, French national credit register and authors' calculations.

3.C Empirical strategy: maximisation program

This appendix displays more precisely the first-order conditions and the maximization program for the WLS estimator : $\min_{\{\alpha_{ft};\,\beta_{bt}\}} \sum_F \sum_B \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}$

WLS estimator: first-order conditions with respect to $\alpha_{f,t}$

$$\frac{\partial \sum_F \sum_B \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}}{\partial \alpha_{f,t}} = 0$$

$$\Leftrightarrow \frac{\partial \sum_B \frac{(CL_{b,f,t}+CL_{b,f,t-1})}{2} \cdot \epsilon^2_{b,f,t}}{\partial \alpha_{f,t}} = 0$$

$$\Leftrightarrow 2 \cdot \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2} \cdot \epsilon_{b,f,t} \cdot \frac{\partial \epsilon_{b,f,t}}{\partial \alpha_{f,t}} = 0$$

$$\Leftrightarrow 2 \cdot \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2} \cdot \epsilon_{b,f,t} \cdot (-1) = 0$$

$$\Leftrightarrow \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2} \cdot \epsilon_{b,f,t} = 0$$

$$\Leftrightarrow \sum_B (CL_{b,f,t} + CL_{b,f,t-1}) \cdot \left(\frac{-\Delta CL_{b,f,t}}{(CL_{b,f,t} + CL_{b,f,t-1})} - \alpha_{f,t} - \beta_{b,t} \right) = 0$$

$$\Leftrightarrow \sum_B -\Delta CL_{b,f,t} - \sum_B (CL_{b,f,t} + CL_{b,f,t-1}) \cdot \alpha_{f,t} - \sum_B (CL_{b,f,t} + CL_{b,f,t-1}) \cdot \beta_{b,t} = 0$$

$$\Leftrightarrow \sum_B \frac{-\Delta CL_{b,f,t}}{(CL_{f,t} + CL_{f,t-1})} = \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1}) \cdot \alpha_{f,t}}{(CL_{f,t} + CL_{f,t-1})} + \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1}) \cdot \beta_{b,t}}{(CL_{f,t} + CL_{f,t-1})}$$

$$\Leftrightarrow \frac{-\Delta CL_{f,t}}{(CL_{f,t} + CL_{f,t-1})} = \alpha_{f,t} + \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{f,t} + CL_{f,t-1})} \cdot \beta_{b,t}$$

$$\Leftrightarrow \Delta^{MPGR} CL_{f,t} = \alpha_{f,t} + \sum_B \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{f,t} + CL_{f,t-1})} \cdot \beta_{b,t}$$

This maximization program indicates symmetrical first-order conditions relative to $\beta_{b,t}$.

WLS estimator: first-order conditions with respect to $\beta_{b,t}$

$$\frac{\partial \sum_F \sum_B \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}}{\partial \beta_{b,t}} = 0$$

$$\Leftrightarrow \frac{\partial \sum_F \frac{\left(CL_{b,f,t}+CL_{b,f,t-1}\right)}{2} \cdot \epsilon^2_{b,f,t}}{\partial \beta_{b,t}} = 0$$

$$\Leftrightarrow 2 \cdot \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2} \cdot \epsilon_{b,f,t} \cdot \frac{\partial \epsilon_{b,f,t}}{\partial \beta_{b,t}} = 0$$

$$\Leftrightarrow 2 \cdot \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2} \cdot \epsilon_{b,f,t} \cdot (-1) = 0$$

$$\Leftrightarrow \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{2} \cdot \epsilon_{b,f,t} = 0$$

$$\Leftrightarrow \sum_F (CL_{b,f,t} + CL_{b,f,t-1}) \cdot \left(\frac{-\Delta CL_{b,f,t}}{(CL_{b,f,t} + CL_{b,f,t-1})} - \alpha_{f,t} - \beta_{b,t} \right) = 0$$

$$\Leftrightarrow \sum_F -\Delta CL_{b,f,t} - \sum_F (CL_{b,f,t} + CL_{b,f,t-1}) \cdot \alpha_{f,t} - \sum_F (CL_{b,f,t} + CL_{b,f,t-1}) \cdot \beta_{b,t} = 0$$

$$\Leftrightarrow \sum_F \frac{-\Delta CL_{b,f,t}}{(CL_{b,t} + CL_{b,t-1})} = \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1}) \cdot \alpha_{f,t}}{(CL_{b,t} + CL_{b,t-1})} + \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1}) \cdot \beta_{b,t}}{(CL_{b,t} + CL_{b,t-1})}$$

$$\Leftrightarrow \frac{-\Delta CL_{b,t}}{(CL_{b,t} + CL_{b,t-1})} = \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{b,t} + CL_{b,t-1})} \cdot \alpha_{f,t} + \beta_{b,t}$$

$$\Leftrightarrow \Delta^{MPGR} CL_{b,t} = \sum_F \frac{(CL_{b,f,t} + CL_{b,f,t-1})}{(CL_{b,t} + CL_{b,t-1})} \cdot \alpha_{f,t} + \beta_{b,t}$$

3.D Empirical strategy: maximisation under normalization

WLS estimator: first-order conditions with respect to $\alpha_{f,t}$

$$
\begin{aligned}
& \frac{\partial \sum_F \sum_B \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}}{\partial \alpha_{f,t}} = 0 \\
\Leftrightarrow\ & \frac{\partial \sum_B \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}}{\partial \alpha_{f,t}} = 0 \\
\Leftrightarrow\ & 2 \cdot \sum_B \omega_{b,f,t} \cdot \epsilon_{b,f,t} \cdot \frac{\partial \epsilon_{b,f,t}}{\partial \alpha_{f,t}} = 0 \\
\Leftrightarrow\ & 2 \cdot \sum_B \omega_{b,f,t} \cdot \epsilon_{b,f,t} \cdot (-1) = 0 \\
\Leftrightarrow\ & \sum_B \omega_{b,f,t} \cdot \epsilon_{b,f,t} = 0 \\
\Leftrightarrow\ & \sum_B \omega_{b,f,t} \cdot \left(\tilde{D}_{b,f,t} - \alpha_{f,t} - \beta_{b,t} \right) = 0 \\
\Leftrightarrow\ & \sum_B \omega_{b,f,t} \cdot \frac{D_{b,f,t}}{CL_{b,f,t-1}} = \alpha_{f,t} \cdot \sum_B \omega_{b,f,t} + \sum_B \omega_{b,f,t} \cdot \beta_{b,t}
\end{aligned}
$$

Specifying the weights $\omega_{b,f,t}$ such that $CL_{b,f,t-1}$, the above simplifies to

$$
\begin{aligned}
& D_{f,t} = \alpha_{f,t} \cdot CL_{f,t-1} + \sum_B CL_{b,f,t-1} \cdot \beta_{b,t} \\
\Leftrightarrow\ & \frac{D_{f,t}}{CL_{f,t-1}} = \alpha_{f,t} + \sum_B \frac{CL_{b,f,t-1}}{CL_{f,t-1}} \cdot \beta_{b,t} \\
\Leftrightarrow\ & \tilde{D}_{f,t} = \alpha_{f,t} + \sum_B \frac{CL_{b,f,t-1}}{CL_{f,t-1}} \cdot \beta_{b,t}
\end{aligned}
$$

This maximization program indicates symmetrical first-order conditions relative to $\beta_{b,t}$.

WLS estimator: first-order conditions with respect to $\beta_{b,t}$

$$\begin{aligned}
&\frac{\partial \sum_F \sum_B \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}}{\partial \beta_{b,t}} = 0 \\
\Leftrightarrow\ &\frac{\partial \sum_F \omega_{b,f,t} \cdot \epsilon^2_{b,f,t}}{\partial \beta_{b,t}} = 0 \\
\Leftrightarrow\ &2 \cdot \sum_F \omega_{b,f,t} \cdot \epsilon_{b,f,t} \cdot \frac{\partial \epsilon_{b,f,t}}{\partial \beta_{b,t}} = 0 \\
\Leftrightarrow\ &2 \cdot \sum_F \omega_{b,f,t} \cdot \epsilon_{b,f,t} \cdot (-1) = 0 \\
\Leftrightarrow\ &\sum_F \omega_{b,f,t} \cdot \epsilon_{b,f,t} = 0 \\
\Leftrightarrow\ &\sum_F \omega_{b,f,t} \cdot \left(\tilde{D}_{b,f,t} - \alpha_{f,t} - \beta_{b,t}\right) = 0 \\
\Leftrightarrow\ &\sum_F \omega_{b,f,t} \cdot \frac{D_{b,f,t}}{CL_{b,f,t-1}} = \sum_F \omega_{b,f,t} \cdot \alpha_{f,t} + \beta_{b,t} \cdot \sum_F \omega_{b,f,t}
\end{aligned}$$

Specifying the weights $\omega_{b,f,t}$ such that $CL_{b,f,t-1}$, the above simplifies to

$$\begin{aligned}
&D_{b,t} = \sum_F CL_{b,f,t-1} \cdot \alpha_{f,t} + \beta_{b,t} \cdot CL_{b,t-1} \\
\Leftrightarrow\ &\frac{D_{b,t}}{CL_{b,t-1}} = \sum_F \frac{CL_{b,f,t-1}}{CL_{b,t-1}} \cdot \alpha_{f,t} + \beta_{b,t} \\
\Leftrightarrow\ &\tilde{D}_{b,t} = \sum_F \frac{CL_{b,f,t-1}}{CL_{b,t-1}} \cdot \alpha_{f,t} + \beta_{b,t}
\end{aligned}$$

* * *

Conclusion Générale

La crise financière de 2008 a précipité les différentes autorités de régulation mondiales à coopérer dans la constitution d'une réglementation bancaire internationale stabilisée et renforcée. Ces échanges ont permis la mise en place des Accords de "Bâle III" sous la coordination du Comité de Bâle. Ce nouveau cadre réglementaire comble ainsi les lacunes du précédent et construit un système bancaire plus résilient, sur les différents socles de la solvabilité, de la liquidité ainsi que de la macroprudentialité. Cependant, les amendements récents introduits dans la transposition de Bâle III au niveau juridictionnel révèlent la nécessité de compléter cette réglementation générale par des exigences spécifiques selon les composantes de l'économie. Face à ces évolutions, l'objectif de cette thèse est de mettre en évidence qu'il est également important que ces normes réglementaires s'ajustent aux acteurs économiques, aux instruments économiques ainsi qu'au contexte économique, dont les caractéristiques diffèrent selon les juridictions qui transposent Bâle III. Par conséquent, cette thèse s'articule autour de trois chapitres, qui abordent respectivement chacune de ces composantes de l'économie.

Principaux résultats et implications de politique économique

Le **premier chapitre** analyse la mise en place d'une mesure réglementaire au niveau européen dans le but de soutenir l'accès au crédit bancaire des petites et moyennes entreprises (PME), qui introduit une réduction de 24% des exigences de fonds propres (EFP) réglementaires associées aux prêts aux PME. En particulier, ce facteur de soutien (FS) est évalué selon deux perspectives : d'une part, la cohérence des EFP avec le risque de crédit induit par les prêts aux PME, d'autre part, l'efficacité de la mesure par l'amélioration de la distribution de crédit aux PME.

Les EFP économiques estimées sur la base d'un cadre multifactoriel indiquent que ces exigences doivent être plus faibles pour les PME que pour les grandes entreprises, confirmant ainsi la cohérence d'une réduction des exigences de capital avec un risque moindre des prêts aux PME. Non seulement les grandes entreprises sont plus exposées au risque systématique que les PME, mais la présence de ces dernières dans le portefeuille total des prêts bancaires offre également un potentiel de diversification réduisant le risque du portefeuille. Finalement, ces estimations révèlent que la différence d'EFP économiques entre les PME et les grandes entreprises est effectivement cohérente avec l'ampleur de la réduction des EFP induite par le FS, ce qui encense particulièrement la légitimité de cette mesure.

S'agissant de l'efficacité du FS, nos résultats révèlent que la distribution de prêts aux PME s'est significativement accrue après la mise en œuvre du FS, comparativement à leur niveau avant la réforme, avec un renforcement de l'impact positif au fil du temps. Ce chapitre souligne aussi l'hétérogénéité de l'impact, plus important pour les petites entreprises que pour celles de taille moyenne, ainsi que pour les PME sans notation de crédit, qui ont plus bénéficié du FS que les PME considérées comme bien notées ou risquées. Enfin, notre analyse révèle que l'effet du FS est non linéaire, en raison du seuil d'éligibilité des expositions. Alors que les expositions éligibles classées comme petites ont fortement bénéficié du FS, les expositions éligibles moyennes et grandes ont diminué dans la période post-réforme.

Les conclusions de ce chapitre confirment donc la cohérence et l'efficacité du FS pour les PME, permettant de pallier le caractère généralisé d'une réglementation qui pénalisait lourdement et arbitrairement l'accès au crédit des PME. Les résultats mettent néanmoins en lumière un aspect dissuasif et limitant de cette mesure, lié au seuil d'éligibilité des expositions, situé à 1,5 million d'euros, qui conduit les banques à n'accroitre leur offre de crédit aux PME que pour les petites expositions. Après la vérification de la légitimité du FS pour les prêts aux PME et la confirmation que l'ensemble des expositions aux PME présente un risque moindre par rapport aux grandes entreprises, ce seuil d'éligibilité des expositions ne se justifie plus.

Le **deuxième chapitre** examine une contribution récente de la réglementation bancaire, relative à la liquidité des banques et présente les bénéfices des exigences élaborées sous une forme contracyclique, que les banques peuvent relâcher et exploiter lorsqu'elles sont confrontées à un choc de liquidité. Nous développons un modèle théorique qui permet d'illustrer l'impact potentiel de la mise en place d'une réglementation relative à la liquidité sur le comportement des banques. Notre modèle indique que lorsque la réglementation est contraignante ou que la liquidité de marché est faible, les banques adoptent un comportement de précaution et accumulent des liquidités afin de faire face aux potentiels chocs de liquidité.

A l'inverse, les banques qui bénéficient de niveaux de liquidité plus confortables, de sorte que la réglementation n'est pas contraignante, déterminent leur allocation d'actifs plus ou moins liquides en fonction de leur rentabilité, en diversifiant leur portefeuille. En ligne avec le modèle théorique, nos estimations empiriques mettent en évidence que la liquidité de marché n'affecte les ratios réglementaires de liquidité et de solvabilité qu'en période de fortes tensions sur les marchés. En particulier, cet effet négatif est plus important sur la liquidité que sur la solvabilité des banques, ce qui confirme l'existence d'interactions dominantes entre la liquidité de financement des banques et la liquidité de marché pendant les périodes de crise. Cette relation non linéaire soutient l'élaboration d'une réglementation de la liquidité contracyclique, favorisant l'accumulation de liquidité en période d'expansion et son utilisation en période de crise, similairement aux coussins réglementaires de fonds propres, afin d'affronter les crises potentielles avec un niveau de liquidité plus solide sur lequel les banques pourront s'appuyer.

Enfin, le **troisième chapitre** confirme l'importance d'une réglementation plus spécifique aux risques que présentent certains instruments de financement. En effet, les caractéristiques des lignes de crédit, et plus concrètement des tirages, peuvent compromettre la capacité de gestion des liquidités des banques. En particulier, nous démontrons tout d'abord l'impossibilité pour les banques de remplir leurs engagements de prêt avec leurs remboursements, illustrée par une très faible corrélation entre ces deux composantes. Si une entreprise rencontre de fortes difficultés de financement, la banque peut ne pas être en mesure de lui fournir des liquidités parce que le total des facilités de crédit engagées dépassera largement les fonds disponibles de la banque provenant des autres entreprises dont le besoin de liquidité ne se matérialise pas au même moment. Deuxièmement, nous mettons en évidence la forte concentration des lignes de crédit et des tirages, qui empêche les banques d'exploiter la diversification de leur portefeuille pour faire face aux tirages. Troisièmement, nous montrons que cette concentration génère une forte volatilité dans les tirages, provenant d'un nombre limité d'entreprises. Ces particularités témoignent de l'importance du risque idiosyncratique induit par les lignes de crédit au sein des portefeuilles bancaires et impliquent que les banques peuvent tomber dans un piège à liquidité à tout moment du cycle économique. Aussi, ce chapitre soutient la nécessité d'appliquer une réglementation adaptée à ces instruments de financement aux risques multiples.

Limites et extensions

Cette thèse présente évidemment certaines limites qu'il conviendra de dépasser *via* diverses améliorations potentielles dans le cadre de nos recherches futures. Le premier chapitre évalue l'efficacité du SF par une comparaison des expositions entre PME éligibles et PME non éligibles. La méthodologie en différence-de-différences établit donc ses groupes de traitement et de contrôle selon le montant des expositions des PME. Cependant, les conditions d'éligibilité au FS sont doubles et nécessitent *(i)* le statut de PME et *(ii)* un montant des expositions inférieur au seuil d'1,5 million d'euros. Notre approche concentrée sur un échantillon de PME, utilisant le seul critère du montant des expositions pour éligibilité, permet donc de renseigner sur l'efficacité du FS au sein de ce groupe, mais n'exploite pas le critère du statut de PME. Il s'agit néanmoins d'une limite volontairement contournée dans la mesure où les PME et les grandes entreprises sont des acteurs de l'économie qui se comportent et réagissent très différemment, dont la comparaison n'est ainsi pas la plus pertinente pour évaluer l'impact de cette réforme.

Le prolongement de l'analyse de cette mesure réside dans la modification annoncée par les autorités réglementaires européennes, par l'application de *Capital Requirements Directive V*, qui relève le seuil d'éligibilité de 1,5 million à 2,5 millions d'euros pour le FS de 24% et ajoute un FS de 15% pour les expositions au-dessus du nouveau seuil d'éligibilité. Malgré l'application d'une réduction des EFP réglementaires pour toutes les expositions des PME désormais, une nouvelle évaluation de cet ajustement de la réglementation, de la mise en place d'un nouveau seuil et d'un échelonnage des réductions des EFP selon le montant des expositions permettrait la confirmation d'une réglementation rigoureusement adéquate.

Le deuxième chapitre présente également des limites, dont certaines contournables pourront faire l'objet d'extensions. Ainsi, notre modèle théorique simplifié, qui n'a vocation que d'illustration dans ce chapitre, pourrait porter un intérêt et des conclusions plus solides si le bilan bancaire et l'hétérogénéité des actifs étaient plus développés, ce qui constituera une prochaine étape de ce projet. Concernant l'approche empirique, l'absence de données suffisantes sur le LCR nous impose l'utilisation d'un ratio de liquidité réglementaire français, proche du LCR mais dont les pondérations sont différentes. La future disponibilité des données de LCR sur une période temporelle plus longue nous permettra de mettre à jour et de renforcer ces résultats par la suite.

Enfin, le troisième chapitre de cette thèse propose des résultats intéressants sur les risques présentés par les lignes de crédit mais reste le moins aboutit, ce qui lui confère un potentiel d'extension plus large. L'analyse se restreint à des statistiques descriptives, déjà très informatives, mais dont une analyse économétrique permettrait d'asseoir les conclusions. En l'occurrence, la méthodologie envisagée, qui produit la décomposition des lignes de crédit et des tirages selon différentes composantes au niveau de la banque et de la firme, permettrait de mieux comprendre les caractéristiques et les implications de l'utilisation de cet instrument, encore méconnues. Par ailleurs, de telles analyses permettraient également de confirmer la dominance du risque idiosyncratique des lignes de crédit parmi les multiples risques que présentent cet instrument de liquidité. La littérature relative au tirage des lignes de crédit étant actuellement peu développée, ce chapitre offre les plus grandes possibilités de recherche futures quant à cet instrument.

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Résumé

Les conséquences de la crise financière de 2008 ont conduit les différentes autorités de régulation mondiales à se coordonner afin de mettre en place une réglementation bancaire plus uniforme dans le but de stabiliser le système financier dans son ensemble et de prévenir les potentielles futures crises à venir. Toutefois, les amendements mis en place au niveau juridictionnel soulignent la nécessité d'établir une réglementation adaptée et ciblée parallèlement à un cadre général et universel. Nous mettons ainsi en évidence l'importance que ces normes réglementaires s'ajustent aux acteurs économiques, aux instruments économiques ainsi qu'au contexte économique auxquels elles s'appliquent.

Dans un premier temps, nous confirmons la pertinence d'une mesure réglementaire permettant une réduction des exigences de fonds propres associées aux prêts aux petites et moyennes entreprises. Les résultats quant à la cohérence et l'efficacité de ce Facteur de Soutien promeuvent l'instauration d'une réglementation adaptée au risque que présentent les acteurs de l'économie. Deuxièmement, par la mise en évidence des interactions entre la liquidité de financement et la liquidité de marché, intervenant en période de stress uniquement, nous démontrons les bénéfices des exigences élaborées sous une forme contracyclique, que les banques peuvent relâcher et exploiter lorsqu'elles sont confrontées à un choc de liquidité. Enfin, nous révélons l'importance d'une réglementation plus spécifique aux risques que présentent certains outils de financement, tels que les lignes de crédit. Leur concentration, leur volatilité et les limites de leur financement confirment la nécessité d'appliquer une réglementation adaptée à ces instruments aux risques multiples.

Alors que la crise a permis d'uniformiser les exigences réglementaires au niveau mondial, nous présentons les avantages d'une réglementation bancaire plus adaptée, avec des exigences globales harmonisées auxquelles viennent s'ajouter des exigences spécifiques lorsque cela s'avère nécessaire.

Mots clés

Réglementation bancaire, solvabilité, liquidité de financement, liquidité de marché, financement des entreprises.

Abstract

The consequences of the 2008 financial crisis led the worldwide regulatory authorities to coordinate their efforts to establish a new global banking regulation with the aim of strengthening the financial system as a whole and preventing potential future crises. However, the amendments put in place at the jurisdictional levels underline the need to establish an appropriate regulation alongside a general framework. In this way, we highlight the importance of regulatory standards adjusting to economic actors, economic instruments and the economic environment.

As a first step, we confirm the relevance of a regulatory measure allowing a reduction in capital requirements associated with lending to small and medium-sized enterprises. The results regarding the consistency and effectiveness of this Supporting Factor promote the introduction of regulation adjusted to the risk generated by economic players. Second, by highlighting interactions between funding liquidity and market liquidity, emerging only during periods of stress, we demonstrate the benefits of requirements developed in a counter-cyclical form, which banks can release and use when facing with a liquidity shock. Finally, we show the importance of more risk-specific regulation of funding tools, such as credit lines. Their concentration, volatility and funding limits confirm the need for an appropriate regulation of these multi-risk instruments.

While the crisis enabled a standardization of regulatory requirements at the global level, we emphasize the advantages of a more specific banking regulation, with aligned global requirements to which suitable requirements are added when necessary.

Keywords

Banking regulation, capital requirements, funding liquidity, market liquidity, corporate financing.