THÈSE DE DOCTORAT
DE
L'UNIVERSITÉ PARIS-SACLAY
PRÉPARÉE À "HEC PARIS"

ECOLE DOCTORALE N° 578
Sciences de l'homme et de la société (SHS)

Spécialité de doctorat: Sciences de gestion

Par

Mr. Charles Boissel

Empirical Essays in Finance

Thèse présentée et soutenue à HEC Paris, à 16 h, le 20 Juin 2018

Composition du Jury :

Monsieur Stefano Lovo	Professeur, HEC Paris	Président du Jury
Monsieur Denis Gromb	Professeur, HEC Paris	Directeur de thèse
Monsieur David Thesmar	Professeur, MIT Sloan	Co-Directeur de thèse
Madame Alberta Di Giuli	Professeure Associée, ESCP	Rapporteur
Monsieur Vicente Cuñat	Professeur Associé, LSE	Rapporteur
Monsieur Laurent Bach	Professeur Assistant, ESSEC	Examinateur

Titre : Essais empiriques en finance

Mots clés : Crise de la zone euro, Secteur bancaire, Culture d'entreprise

Résumé : Cette thèse réalisée au sein du département finance d'HEC Paris est constituée de trois parties. La première s'intéresse à la résilience des chambres de compensation en temps de crise. C'est un travail réalisé avec François Derrien, Evren Ors et David Thesmar dans lequel nous montrons que le manque de régulation de ces acteurs conduit à une détérioration de la confiance qui leur est accordée quand les conditions macroéconomiques se détériorent. Ceci impacte alors négativement leur capacité à assurer une liquidité suffisante sur le marché interbancaire.

Le deuxième chapitre porte sur l'impact de la concentration du secteur bancaire autour de quelques grands groupes sur l'allocation macroéconomique du crédit. J'y développe une approche innovante pour répondre à cette question et montre que cet impact est limité: les chocs idiosyncratiques des "big players" n'ont qu'un rôle limité dans la fluctuation du crédit aggrégé.

La dernière partie est un travail réalisé avec Adrien Matray et Thomas Bourveau. Nous nous intéressons à la transmission de la culture du risque au sein du secteur bancaire et montrons que les filiales d'un groupe bancaire tendent à converger quant à leur évaluation du risque futur. En retour, cela peut amener à une sous-évaluation de ce dernier et impacter la stabilité financière.

Title : Empirical essays in finance

Keywords : Eurozone crisis, Banking, Corporate Culture

Abstract : This thesis is divided into three chapters. The first one deals with Central Clearing Counterparties (CCPs) and their resiliency in crisis times. This is a joint work with François Derrien, Evren Ors and David Thesmar. Focusing on CCPs backed repo trades during the eurozone crisis, we show that the market factored in the default of CCPs. In turn, this affected their capacity to ensure liquidity in the interbank market. Our results have strong consequences for the way CCPs should be regulate.

The second chapter aims at quantifying the impact of the rise of the concentration in the banking sector on aggregate credit fluctuations. Building on novel empirical approach, I show that big players' idiosyncratic shocks have a limited impact on aggregate credit. The explanation lies in the fact that the strength of banking groups idiosyncratic shocks is limited compared to aggregate and subsidiaries level ones.

The last chapter, a joint work with Thomas Bourveau and Adrien Matray, focuses on the transmission of corporate risk culture. We show that subsidiaries of the same banking group tend to assess future risks in similar ways. In turn, this gives insights on how banking crisis can spread be fueled by corporate risk culture.

Acknowledgments

This thesis is the result of a wonderful and enriching travel inside the worlds of academia and finance. This journey had its base station: HEC Paris finance department. There I could always find the support, advices and help that I needed. I could also have long debates and discussions with some of the brightest minds I have ever met. If finance was obviously our preferred topic, politics and political philosophy were hotly debated. This unique atmosphere uniquely fulfilled my intellectual curiosity. For all of that, I am deeply grateful when I look back at the past 5 years. I thank all the faculty members for the advices and feedbacks they gave me throughout my PhD.

I'd like first to thank Laurent Bach, Vicente Cuñat, Alberta Di Giuli and Stefano Lovo for being part of my committee. This is a great honor.

I would not be writing those lines if I hadn't met David Thesmar while I was still a MSc student trying to understand the arcanes of private equity. David encouraged me into pursuing a PhD and has been my PhD supervisor since then. From him, I learned to "think big" according to the highest intellectual standards. David has had a profound impact on my intellectual developmnent which is something I will always be thankful for.

Later on, I had the chance to cross the path of Denis Gromb who kindly accepted to supervise my PhD thesis at a time when David was joining the MIT. Being one of the kindest person I have ever met, Denis has offered me tremendous support and attention in the home stretch of my PhD. I am forever indebted to him. A special thought for his 6pm calls from his drive home, which have been a landmark of my final years at HEC.

Behind HEC Paris PhD program there is a fantastic team that has helped me so many times that I can not thank them enough. People who know me are aware that I am not the best, to say the least, at keeping up with deadlines, filling up forms or handing in administrative documents. However, I have always found the help that I needed at HEC. Britta Delhay, Caroline Meriaux, Celine Rimbault, Melanie Romil : thank you very much! Françoise, thank you very much for your help especially in the past few months. Isabelle, thank you for all the ci......... I hope that we will finally meet for a drink in La Trinite. Christelle, thank you so much for everything you have done for me. I would also like to thank Elie Matta and Ulrich Hege for their guidance and attention while they were at the head of the PhD program.

To Francois Derrien, Johan Hombert and Evren Ors, I would like to say that I will never forget all the time you took to help me writing this thesis. I had the chance to work directly with Francois and Evren, along with David, on a paper that is part of my PhD. This experience has been instrumental in me learning to do research. I thank you very much for your patience and the opportunity you gave me to work with you and present at top conferences (and working on my accent at 10pm in an hotel room in Atlanta). I learned a lot from you and will forever be indebted to you. Johan, even though we never worked on a paper together, you have always been here to discuss my papers and ideas. I thank you depply for your kindness and your comments.

This PhD also owns a great deal to Adrien Matray and Thomas Bourveau. They have been two great co-authors with whom it has been a pleasure to work and debate. In addition to that, they have also become friends. Adrien, I have learned to know you quite well during those years and hope that our ”18th aperos” along with our endless conversations will go on for a long time.

In 2015/2016, I had the chance to spend one year at Harvard University. I would like to thank Andrei Shleifer and Robin Greenwood for welcoming me there and giving me the chance to spend a year in a wonderful environment. I have a special thought for Boris and Anna Vallee who made my year much easier. Thank you Boris for all the discussions we had, the help you gave me and for sharing your office with me. Thank you to both of you for inviting me over and the fun we had. A final tought for Paul Adrien Hippolyte, Marion Baudier-Melon, Alexandre Leandri and Nina Roussille: it was a pleasure to meet you.

Of course, HEC Paris PhD program would not be the same without its PhD students. Pekka Honkanen, Jean-David Sigaux, Thorsten Martin, Marina Traversa, Huan Tang, Yapei Zhang, Victoria Slabik I spent a marvelous time around you. I entered the program along with Sylvain Catherine. Saying that Sylvain and I do not share the same political opinions is an euphemism. But now is the time to say it: Sylvain, I am truly grateful to have met you and deeply respect your intellectual rigour. We have had countless political philosophy discussions which will mark me forever. We were later joined by Etienne Rochon. It has been a pleasure to meet you Etienne. I hope that our nightly discussions about politics (and life) will not stop soon. A final word for Victor Lyonnet with whom I shared an amazing experience, lost somewhere deep down in Seine et Marne.

When doing a PhD, one needs support the academic world. And I have had the chance to be surrounding by friends who have always been here for me. Caroline and Edouard Richard, Nicolas et Morgane Bertozzi, Mickael et Anna Puigmal, Vladimir Bonafoux, Wladimir Mauhin, Marine D'Halluin, Clement Keufer, Emile Bitard, Paul Guerrero, Fabien Garnier and Anne Lacroix: thank you for all those years of friendship. I discovered the world of economy with Elsa Faivre, Sarah Fleche, Elodie Morival, Esther Delbourg and Timothee Jaulin. From my previous studies, I had the chance to meet Kristell Leguern, Guillaume Juan, Romain Frecenon, Lucie Lisant, Clement Champiat, Celine Thiriat with whom I shared so many experiences. A special thought to Jerome Ors with whom I have shared the most interesting correspondence throughout all this years. To Pierre and Morgane Barthalon, I would like to say thank you for all the wonderful time we spent together in Brittany. Pierre has been the exception among my friends as he was nearly the only one (with Nicolas) that could understand what I was doing as a PhD student. This led us to countless debates and discussions, which have had a deep impact on my work. Pierre Marie Goimard, thank you for everything, you are an example. Mathilde Faugere, in addition to be a great friend and a dedicated confident, has been my PhD alterego for all those years. Mathilde, I can't wait to read (the acknowledgements) of your own thesis. To Nicolas Hayon, juste one thing: I don't know how I can thank you enough for everything you have done for me since we met (and for being my partner in fun).

My final thought will be for my family. In addition to my Grand Mother, cousins, aunts and uncles, I would like to thank my Great Father: I don't think that I will ever have done this PhD without your wednesday afternoon's classes back in high school (instead of playing RA2 with Edouard...). Laure and Louise, you witnessed the very beginning of this PhD while you were hosting me ("just for one night, without any questions"). Thank you for everything Sisters. My Parents have been incredibly supportive of my singular way of living my (professional) life. To them I'd like to say that "Here comes the third doctor!".

Thank you all!

Resume en Français

Cette thèse se compose de trois parties s'articulant autour des thèmes suivants: la résilience des chambres de compensation en temps de crise, l'impact de la concentration du secteur bancaire sur les fluctuations du crédit et la transmission de la culture d'entreprise.

Chambres de compensation et résilience

Les chambres de compensation (CCPs) sont des institutions financières dont le rôle est de mutualiser les risques de contreparties en s'insérant entre un prêteur et un emprunteur. En effet, lors d'une transaction effectuée via une CCP, le prêteur prête l'argent à la CCP, et l'emprunteur emprunte à la CCP. Cette dernière assure donc le prêteur contre le risque de défaut de l'emprunteur. Les CCPs permettent ainsi d'augmenter la liquidité disponible, en particulier sur le marché interbancaire.

Depuis la crise de 2008, le rôle des CCPs a été renforcé par les régulateurs européens et américains dans l'espoir que ces dernières favorisent la résilience des marchés financiers en situation de crise. Cette centralisation du marché autour d'un nombre restreint de CCPs s'accompagne cependant d'une attention particulière quant à leur propre capacité à fonctionner en temps de crise.

C'est à ceci que nous nous intéressons avec François Derrien, Evren Örs et David Thesmar dans la première partie de cette thèse. Pour ce faire, nous analysons le comportement des acteurs financiers vis à vis des CCPs pendant la crise de la zone euro. De manière plus précise, nous testons empiriquement l'évaluation du risque de défaut des CCP spar les marchés financiers.

Pour ce faire nous nous concentrons sur l'analyse empirique du marché des "General Collateral" (GC) repos sur la période 2008-2012. C'est un marché de prêts collatéralisés par des titres de dettes souveraines issus par des pays de la zone euro. Toutes les transactions sont anonymes et centralisées via une CCP.

Sur ce marché, un emprunteur dépose un collatéral, dont la valeur est supérieure au montant emprunté, auprès de la CCP. La CCP lui prête en échange de l'argent provenant d'une autre institution. En cas de défaut de l'emprunteur, la CCP peut revendre le collatéral et rembourser le prêteur. Si la valeur du collatéral s'est détérioriée au moment du défaut, dans le cas d'un défaut souverain simultané par exemple, la CCP peut puiser dans ses fonds propres[1]

Nous basons notre analyse sur ce que je viens de décrire et un modèle simplifié qui formalise l'intuition suivante:

- Tant qu'un prêteur a confiance dans la capacité de la CCP à le rembourser dans le cas d'un défaut de l'emprunteur et d'un défaut du souverain ayant émis le collatéral, alors le taux auquel il prête sur le marché repo ne dépend pas de la qualité du collatéral (puisqu'il a confiance en la capacité de la CCP de le rembourser).
- Dans cette situation, il n'éxiste pas de corrélation entre le taux sur le marché repo et le risque du collatéral. Empiriquement, si l'on régresse le taux auquel est prêté de l'argent sur un indice de risque d'un titre de dette souveraine (son Credit Default Swap, CDS), alors le coefficient est proche de zéro.
- A l'inverse, si la CCP est considérée comme risquée, c'est à dire qu'elle ne disposerait pas des ressources nécessaires pour rembourser le prêteur en cas de défaut du prêteur et du souverain, alors le taux d'emprunt va fluctuer en fonction du risque du souverain (CDS).
- Dans ce cas, le taux repo devient positivement corrélé avec le CDS du collatéral

Pour tester notre intuition, nous nous basons sur des données journalières acquises auprès de deux des principales plateformes d'échanges électroniques européennes (ICP BrokerTec et MTS repo) couvrant la période 2008-2012. Les données dont nous disposons couvrent les GC repos effectués

[1] La réalité est un peu plus compliquée la CCP peut aussi eventuellement avoir recours à des dépôts d'autres participants.

via ces plateformes. Par souci de simplicification, notre analyse couvre par ailleurs les seuls prêts au jour le jour.

Nos résultats indiquent qu'au pic de la crise de la zone euro la confiance des prêteurs vis à vis des CCPs s'effondre. En conséquence, la capacité des CCPs à remplir leur rôle est négativement impactée. Seule l'intervention de la Banque Centrale Européenne à travers le LTRO fut capable de rassurer les marchés financiers.

Nous concluons en prônant une meilleure régulation de ces dernières (niveau minimum de capital, transparence) ce qui permettrait de s'assurer que les CCPs gardent l'entière confiance des institutions financières au moment où leur activité est essentielle: lorsque les conditions sont particulièrement défavorables.

Concentration bancaire et fluctuations du crédit

Les pays développés ont connu une augmentation très forte de la concentration du secteur bancaire depuis les années 80. Aux Etats-Unis, les 5 plus grosses banques détiennent approximativement 50% des actifs bancaires du pays. La second partie de cette thèse s'intéresse à l'impact d'un tel niveau de concentration sur les fluctuations macroéconomiques du crédit.

Certains travaux défendent l'idée que ceci a un impact sur la volatilité de ce dernier en exposant les économies aux chocs idiosyncratiques des plus grosses banques. L'idée est la suivante: une économie composée d'une multitude de petites banques n'est que peu exposée aux décisions d'allocation de crédit d'une banque donnée. Les raisons de l'évolution du niveau aggrégé des prêts est alors à trouver dans des chocs macroéconomiques (récession, boom, crise) sans que l'on puisse en imputer la responsabilité à aucune des banques.

A l'inverse, dans une économie où il n'existe qu'un tout petit nombre de banques, alors chacune d'entre elles expose potentiellement l'économie toute entière à ses propres décisions, ou chocs idiosyncratiques.

Dans le second cas, le risque est que la volatilité du crédit augmente par rapport à une situation où le marché bancaire serait plus équitablement réparti, les chocs idiosyncratiques affectant les banques devenant des facteurs majeurs de l'explication des mouvements de l'offre de crédit. Il s'en suit par ailleurs que plus la force de ces derniers est importante et plus leur impact sur l'allocation de crédit le sera.

L'impact de la concentration bancaire sur la volatilité du crédit dépend donc de deux facteurs: la part de marché des plus grands groupes et la force des chocs qui leur sont propres. Si la taille est un facteur directement observable dans les données dont nous disposons, une estimation de la force des chocs idiosyncratiques, et plus précisément de leur variance, est empiriquement difficile mesurable.

La contribution de cet article est de développer une nouvelle méthode empirique pour estimer cette valeur de manière à pouvoir répondre à cette question. L'intuition est la suivante: la force des chocs idiosyncratiques spécifiques à une groupe bancaire peut être déduite en examinant le niveau de corrélation de l'allocation de crédit de ses différentes filiales. Pour illustrer cette proposition, on peut considérer les situations suivantes:

- Soit un groupe bancaire dont les filiales se comporteraient de manière totalement indépendantes: dans ce cas leur décisions de prêts ne seront que peu corrélées. Le groupe se comporterait alors comme une collection de banques de petites tailles et la valeur des chocs spécifiques au groupe serait simplement nulle. Dans ce cas, la concentration du secteur bancaire n'aurait pas d'impact sur la volatilité du crédit.

- Soit un groupe bancaire dont les dirigeants décident eux-mêmes des montants que ses filiales prêtent. Sous cette hypothèse les décisions d'allocation des différentes unités du groupe seront fortement corrélées. En conséquence, les décisions prises par ses dirigeonts auront la capacité de fortement impacter le crédit alloué au niveau macroéconomique, si tant est que la taille du groupe est suffisante.

Le problème que je soulève ici est donc que la structure des groupes et l'indépendance relative des différentes filiales leur appartenant sont les facteurs déterminants de la force des chocs spécifiques aux groupes bancaires.

Empiriquement parlant, la mesure de l'impact précis d'un groupe sur la corrélation des allocations de crédit de cette filiale est délicate. D'autres facteurs pouvant influencer cette corrélation (en cas de crise, toutes les banques prêtent moins par exemple qu'elles appartiennent ou non à un groupe), il faut pouvoir isoler l'effet spécifique d'appartenir à un groupe. Pour ce faire j'étudie le comportement des filiales avant et après leur acquisition par un groupe.

En comparant le changement de la corrélation de l'allocation de crédit entre une filiale nouvellement acquise et les autres filiales du groupe, avant et après son acquisition, je suis en mesure d'estimer précisément l'influence qu'un groupe a sur les décisions de prêts de ses filiales.

En utilisant des données sur l'ensemble des banques américaines sur la période 1980-2010, dans lesquels j'identifie l'ensemble des acquisitions réalisées au cours du temps, je suis en mesure d'appliquer cette méthode et d'obtenir une estimation précise de l'indépendance relative des différentes unités d'un groupe, et ainsi de la force des chocs idiosyncratiques affectant les groupes bancaires.

Il résulte de cette analyse que cette dernière n'est pas aussi grande que l'on aurait pu le penser. En d'autres termes, l'indépendance relative d'une filiale quant à ses décisions d'allocation de crédit, vis à vis du groupe auquel elle appartient, est forte. Je conclus donc que malgré le niveau très élevé de concentration du secteur bancaire, l'impact des plus grands groupes sur les fluctuations du crédit aggrégé est limité.

Transmission de la culture du risque

Les questions relatives à l'existence d'une culture d'entreprise, et son éventuel impact économique, sont largement débattues dans la littérature. La difficulté de ces recherches est cependant que la nature même de ce facteur le rend très difficile à approcher empiriquement.

Dans la troisième partie de cette thèse, co-écrite avec Thomas Bourveau et Adrien Matray, nous utilisons la méthode empirique développée au deuxième chapitre pour dépasser ce problème.

Plus particulièrement, nous nous intéressons à la manière dont les acquisitions modifient l'évaluation du risque de leurs actifs par les cibles. Les acquisitions sont donc ici utilisées comme choc sur la culture du risque d'une entreprise (banque) existante. La question est donc de savoir si la banque acquérant une nouvelle filiale transmet sa propre culture du risque et si nous sommes en mesure de le mesurer.

Pour tester notre hypothèse, nous comparons l'évolution de la corrélation du niveau des "Provisions pour Pertes sur Prêts" (PPPs) entre une banque nouvellement acquise et les autres filiales du groupe l'intégrant, avant et après son acquisition. Cette approche est similaire à celle du chapitre 2, tout comme les données utilisées pour la mettre en oeuvre, mais elle est ici appliquée à un sujet différent. Le choix de se concentrer sur les PPPs comme une mesure empirique de la culture de risque s'explique par deux raisons. La première est que c'est une mesure hautement subjective: elle est donc susceptible de reflèter les variations dans la culture de risque existant au sein d'une banque. La deuxième raison est que les PPPs sont un facteur majeur de la gestion des risques d'une entreprise.

Les résultats des premières analyses montrent clairement qu'il y a convergence dans l'évaluation du risque futur suite à l'acquisition. La banque nouvellement acquise se rapproche des pratiques de la banque acquérante. Nous testons ensuite deux prédictions construites à partir de la littérature existante sur ce sujet. La première est que la transmission de culture sera d'autant plus importante si la proximité géographique entre l'acquéreur et la nouvelle filiale est proche. La seconde est que cette transmission est contingente au pouvoir de négociation de l'acquéreur, que nous approximons en comparant la taille relative de la filiale par rapport à celle du groupe. Ces deux prédictions sont validées par nos analyses empiriques, contribuant ainsi à une compréhension plus fine du processus de diffusion de la culture d'entreprise.

Introduction

This thesis deals with three different topics: CCPs resilience in times of market stress, the role of big banks in the fluctuations of aggregate credit and the transmission of corporate risk culture.

Central Clearing Counterparties and financial stability

Central Clearing Counterparties (CCPs) are key to the functionning of modern financial markets. By inverting themselves between two financial institutions, they eliminate counterparty risk. By doing so, CCPs increase financial stability. In this paper, we focus on CCPs backing the European repo market, and more especially the General Collateral (GC) segment of this market. There, sovereigns bonds are used as collateral to borrow from CCPs. Loans are overcollateralized by a given percentage (the haircut) and generally short term (overnight). Acceptable collateral is published by a CCP, along with corresponding haircuts. Given the structure of the loan, interest rate on the CCP backed GC repo market is close to the safe rate of return.

The use of CCPs has been advocated by financial regulators worldwide in an effort to stabilize market liquidity, especially in times of market stress. However, little is known about their capacity to withstand extreme financial shocks. Indeed, when markets conditions deteriorate, collateral risk increase which in turn may affect the trust of markets participants in the CCP.

To study this aspect, we focus on the eurozone CCP GC repo market around the 2009-2010 sovereign crisis. Building on a large datasets of repo transactions for the period 2008-2012, we are able to analyse the market reaction to a worsening collateral quality.

We find that CCPs offer protection against risk fluctuations in times of moderate market stress repo rates do not respond to small changes in sovereign bonds credit risk. However, at the peak of the eurozone crisis, trust in the CCP financial capacity to cope with a sovereign default vanishes. In turn, participants factor in the probability of a CCP default and repo rates become sensitive to the underlying collateral quality. CPPs no longer seem to offer a sufficient protection to lenders and interbank liquidity deteriorates.

We therefore conclude that "CCPs are not a panacea". They can not protect againt aggregate risk. Regulators should therefore improve the regulation of CCPs to ensure that trust in CCPs remains strong even when overall conditions worsen so that they can continue to provide liquidity to the interbank market.

Big banks and their effect on aggregate credit conditions

Since the 80's, the banking sector witnessed a huge increase in concentration. A few big players now account for a large share of market in most western countries. In the US, the top 5 banking groups own more than 50 % of the country banks' assets. Such a high level of concentration may expose entire economies to idiosyncratic shocks of a few big players, decreasing overall financial stability.

Gabaix (2011)[2] was the first to attract attention to this issue. Studying the correlation between top firms activity and country level GDP, he argues that idiosyncratic risk is of the biggest firms is a key factor of economic fluctuations. I build upon his framework and adapt it to the banking sector.

My findings are at odd with his. Using data on the US banking sector covering more than 30 years, I find that the impact of the biggest banking groups seem to be mitigated. The intuition behind this result is that the different subsidiaries of a given banking group largely behave as if they were independent from each other. In turn, group level idiosyncratic shocks only marginally

[2] Gabaix, Xavier. "The granular origins of aggregate fluctuations." Econometrica 79.3 (2011): 733-772.

affect individual entities. Thus banking groups are in fact similar to a collection of smaller banks, and the overall economy is globally insulated from group level shocks.

To reach this conclusion I develop a novel empirical strategy. I use acquisitions of new subsidiaries by existing groups and measure the evolution of lending growth comovement between the newly acquired branch and the others units of the acquirer. by doing so I am able to recover an estimate of banking groups idiosyncratic shocks' strength: the higher it is, the higher the rise of lending comovement after acquisition. If on the other hand subsidiaries behave like independent entities, then the rise in comovement will stay limited and the group structure will be transparent for the overall credit allocation.

The results of this empirical anaylisis show that even though lending comovement does rise after the acquisition, thus validating the very existence of idiosyncratic shocks at the group level, this rise is not sufficient to significantly affect aggregate lending. Aggregate risk remains the major driver of credit fluctuations.

The transmission of corporate culture

In the last chapter of this thesis, co authored with Thomas Bourveau and Adrien Matray, we build upon the above presented empirical strategy to study how corporate culture may spread within different business units. As stated previously, when a bank is integrated into a banking group, its becomes affected by group level shocks. In this work, we go a step further and look at a hotly debated topic in economics and finance: the transmission of corporate culture.

Namely, when a bank is newly acquired by a group it becomes expose to the group corporate culture. However, measuring culture is an empirical challenge in itself. Building upon the existing litterature, we focus on an established proxy of corporate risk culture: discretionary risk assessment, measured using Loan Loss Provisions (LLPs). Our hypothesis is that if corporate risk culture is transmitted to a newly acquired subsidiary, then one should observe a convergence of its own risk assesment with the one of others subsidiaries.

Looking at LLPs comovement before and after the acquisition of new unit, we find that this is indeed the case: risk assessment policy synchronization increases. We further find that this transmission of risk culture increases when geographical proximity between the group and the newly acquired subsidiary is small and its bargaining power is low. This contributes to our overall understanding of how corporate culture impact firm level decisions and to the role of banking groups risk policy in the build-up to the 2008 financial crisis.

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Chapter 1

Systemic Risk in Clearing Houses: Evidence from the Repo Market

Joint with Francois Derrien (HEC Paris), Evren Ors (HEC Paris) and David Thesmar (MIT)

1.1 Introduction

Central clearing counterparties (CCPs) are a fundamental component of the infrastructure of modern financial markets. In normal times, CCPs eliminate counterparty risk by inserting themselves between the buyer and the seller of an agreed-upon trade. They do so in exchange of imposing a collateral-specific haircut to member institutions, a contribution to their "default fund", and concentration limits (Duffie, 2015). As such, CCPs can help increase financial stability. But they are no panacea: While CCPs mutualize idiosyncratic counterparty risk in many ways, they remain vulnerable to financial crises. Given their size and centrality in the functioning of financial markets, their ability to withstand extreme financial shocks has become a first-order concern for all regulators around the world (e.g., Tucker, 2011; BIS, 2012; ISDA, 2013; Coeuré, 2014; DTCC, 2015). There is, however, little empirical evidence on how CCPs actually behave in times of crisis, and this study is an attempt to fill this gap.

In this paper, we examine how the CCPs backing the European repurchase agreement (repo) market were affected by the Eurozone crisis of 2008-2012. In this market, sovereign bonds are used as collateral by banks to borrow overnight. This collateralized interbank lending market, which has become very large in recent years, with a daily volume of about €220bn that correspond to 55% of total secured lending in the Eurozone (2012 ECB Money Market Study), is crucial for the mutualization of liquidity shocks across banks. When sovereign crises arise, government bonds become worse collateral. This can affect the borrowing conditions on the repo market, which may in turn reduce interbank liquidity and weaken the banking system, as in Martin, Skeie and Von Thadden (2014). To mitigate such contagion, regulators have recently pushed market participants to systematically use CCP-cleared transactions.

To examine whether the European sovereign debt crisis led to the build-up of stress in a major CCP, we focus on one large segment of repo transactions called "General Collateral" (henceforth GC). In this segment cash lenders commit to accept as collateral any bond from a given sovereign (e.g., "Italian GC")[1].1 The focus on GC ensures that market participants in our data are banks

[1] Albeit with CCP-imposed haircuts that vary by the sovereign and the maturity of the underlying collateral.

conducting transactions for cash management purposes. Our data cover the 2008-2012 period, and come from two trading platforms that match repo transactions anonymously. These trades are then cleared via CCPs. Our sample covers a sizable part of the European GC repo market: In our data, the daily volume is close to €50bn on average, compared to a total volume of CCP-cleared European interbank repos of about €120bn (Fig. 1)[2].

Our null hypothesis is that the CCP offers perfect protection against risk fluctuations of the underlying collateral. To test it, we measure the extent to which shocks to sovereign collateral affect the repo rate. In a nutshell, our findings are consistent with the CCP-cleared repo market being immune against moderate sovereign stress. In times of extreme sovereign stress, however, repo market participants appear to factor-in into their repo pricing the higher probability of CCP default conditional on sovereign default. Interestingly, increases in collateral-specific haircuts imposed by the CCP have no impact on the repo market, maybe because the instituted haircut changes are not sufficiently large.

To structure our empirical tests, we first develop a simple theoretical framework, in which cash lenders in a repo transaction have some exposure to collateral (sovereign bonds in our case). We use this model to formalize the relation between sovereign CDS spreads and repo rates, making the simplifying assumption that the cash lender expects to own the sovereign collateral if the CCP defaults. The model shows that this relation is stronger when (1) the default risk of CCP member financial institutions conditional on sovereign default increases, (2) CCP risk conditional on CCP member and sovereign defaults increases, and (3) haircuts are not high enough to eliminate these increases in risk. When, however, investors do not expect the CCP to default at all, the framework shows that the repo rate should not be sensitive to the sovereign CDS spread: This is our null hypothesis.

We, then, go to the data. In times of "moderate sovereign stress" (2009-2010), we are indeed unable to reject our null hypothesis: Repo rates are uncorrelated with the CDS spread of the underlying sovereign. In "high sovereign stress" times (2011), however, repo rates become strongly correlated

[2] The interbank market is mostly constituted of secured (i.e. bilateral or trilateral repo) transactions. By comparison, the average daily volume on the unsecured interbank market is about €60bn (ECB Money Market Study, 2012).

with CDS spreads. This relation is concentrated in the countries that were affected the most by the crisis, namely, Greece, Ireland, Italy, Portugal and Spain (hereafter, GIIPS countries). The same relation does not exist for the other Eurozone countries. We also find a similar negative connection, albeit weaker, between repo volume and CDS spreads. All in all, our findings suggest that in 2011 the repo market participants priced CCP default. This stopped to be the case in the first half of 2012.

Next, we use our simple framework to decompose the 2011 stress of the repo market into the contributions of (1) haircuts, (2) CCP members' default risk, and (3) CCP default risk. Our decomposition suggests that investors perceived CCP protection to be fully effective in 2009-2010, but highly ineffective at the peak of the sovereign crisis in 2011. First, we look at the effect of haircuts, which in our model should reduce the connection between repo rates and CDS spreads. To evaluate the effectiveness of haircut policies, we run event studies around large changes in haircuts. We find that in 2011, haircut changes have no effect on the relation between sovereign CDS spreads and repo rates. We infer that changes in haircuts put in place by the CCP were not effective (i.e., not large enough) to stem the adverse movements in repo rates for GIIPS countries. Second, we look at changes in CCP member default risk conditional on sovereign default risk. We estimate this parameter by regressing bank CDS spreads on sovereign CDS spreads. We find that the risk of CCP member failure conditional on sovereign default risk does not increase between 2010 and 2011. Hence, if the repo market appears more stressed in 2011, this does not seem to come from the fact that CCP-member banks became riskier in the event of sovereign default. Thus, it must be the case that investors perceived the risk of CCP failure (measured as the default probability conditional on sovereign and member default) as being higher in 2011 than in earlier years. To confirm that the CCP was seen as offering little protection in 2011, we estimate the repo rate-to-sovereign CDS spread relation separately for a sample of bilateral trades that go through the same trading platform but are not cleared by the CCP. We find that in 2011, repo rates in CCP-based trades were not less sensitive to sovereign CDS spreads than repo rates in bilateral trades. This suggests that, at that time, investors estimated CCP default risk to be similar to counterparty risk in bilateral transactions.

We provide several robustness tests and examine alternative explanations for our findings. In particular, we show that the haircut policy of the ECB, which uses the repo market to conduct its monetary policy operations, does not explain our findings. We also explore a monopoly power explanation, in which concentrated lenders facing cash-short borrowers with collateral from GIIPS countries, can impose high borrowing rates on the repo market in 2011. The evolution of supply and demand on the repo market suggests that this is unlikely to be the main driver of our results. Additional tests also rule out liquidity funding risk as the main driver of our results: Our main finding remains unaffected when we add proxies for liquidity crunch (e.g., outstanding Certificate of Deposit (CD) volume) in our main regressions.

Our paper contributes to the nascent literature on the role of CCPs, which focuses exclusively on derivatives clearing. New regulatory frameworks, such as Frank-Dodd in the US and EMIR in the EU, require that more OTC trading to go through CCPs as the latter provide insurance against counterparty default at lower collateral cost. This is because CCPs are multilateral, and thus allow internalizing default externalities (Koeppl, Monnet and Temzelides, 2012; Acharya and Bisin, 2014) and efficient use of collateral (Duffie and Zhu, 2011; Duffie, Scheicher and Vuillemey, 2015). But while CCPs provide efficient protection against idiosyncratic counterparty risk, they offer no intrinsic protection against aggregate risk and may even encourage risk-shifting (Biais, Heider and Hoereva, 2012). Due to their size and connections, they are likely to be systemically important and thus need to be monitored. Although recent papers have proposed econometric methods to estimate CCP risk, these have focused on derivative trading (Jones and Pérignon, 2013; Menkveld, 2015). Our paper develops an alternative approach to estimate the extent of CCP stress in the data, in the context of repo transactions. Our method relies on the idea that market participants expect, in case of CCP default, that they will be exposed to the sovereign collateral. This is admittedly a strong assumption about the liquidation process, as the sharing of losses among CCP members in case of default was not very well defined during the period studied (Bank of England, 2011; Duffie, 2015; DTCC, 2015). It is however consistent with Variation Margin Gains Haircuts (VMGHs) advocated by many experts in recent years.

This paper also belongs to the larger literature on the repo market, in particular repo transactions motivated by cash lending or borrowing (as opposed to shorting of particular securities). Most recent work in this area has focused on the evolution of the US repo market during the 2008-2009 crisis (Gorton and Metrick, 2012; Copeland, Martin and Walker, 2014; and Krishnamurty, Nagel, and Orlov, 2014). The European repo market is different in two dimensions. First, while the US market is dominated by triparty repo (in which settlement, but not counterparty risk, is managed by a third party), transactions conducted on electronic platforms and cleared via a CCP predominate in Europe. However, both markets are similar in that they resisted well the financial crisis, with no significant decline in volume (see our Fig. 1 and Copeland, Martin, and Walker, 2014). Second and most importantly, the European repo market is the main segment of the European interbank market, unlike in the US where the unsecured Fed Funds market dominates (Afonso, Kovner, and Schoar, 2011). The European repo market is a key part of the interbank market where the ECB conducts its conventional and non-conventional monetary operations[3]. While several papers study its stability via the network structure (see for instance Gai, Haldane, and Kapadi, 2011), our focus is different. In Europe, because public debt is the most common source of collateral on the repo market, sovereign crises have an additional power to contaminate the banking system[4]. The recent regulatory push towards centrally-cleared transactions is an attempt to break the doom loop between sovereigns and their banks. Our paper is a tentative evaluation of the possibility that CCPs may be a focal point of stress rather than a source of stability for the European interbank market, at least in extreme circumstances (see also Mancini, Ranaldo, and Wrampelmeyer, 2015 on this topic).

The paper proceeds as follows. Section 2 describes the European repo market, data sources and variables used in the analysis. Section 3 presents our conceptual framework. Main results are in Section 4. In Section 5, we propose and test several explanations for the link between sovereign CDS spreads and repo rates. Section 6 discusses alternative explanations for our findings and Section 7 concludes.

[3]Several papers examine the microstructure of the ECB's main refinancing operations in normal vs. crisis times (Bindseil, Nyborg, and Strebulaev, 2009; Cassola, Hortaçsu, and Kastl, 2013; Dunne, Fleming, and Zholos, 2011, 2013).

[4]This mechanism can contribute to the link between banks and sovereigns as more broadly discussed in several recent papers (Acharya, Dreschler, and Schnabl, 2014; and Gennaioli, Marin, and Rossi, 2014), which focus on other transmission mechanisms.

1.2 Institutional background and data

1.2.1 The repo market

We focus on the role of CCPs in managing GC repo transactions that are electronically and anonymously matched. We start with a brief description of this market.

A repo is a loan collateralized with a security. Both parties (the cash lender and the security owner) agree on an interest rate, a maturity, and a haircut. The maturity is typically short (in our data, one day). The haircut is the percentage difference between the value of the security and the loan size (it is positive, i.e., the loan is over-collateralized). Hence, the interest rate is close to the safe rate of return. It may, however, fluctuate as a function of collateral risk, bank risk and insufficient haircut adjustments (see below).

We restrict our analysis to GC repos. Repo transactions are typically classified into "general collateral" and "special". The latter are loans against a specific collateral (e.g., "Italian fixed-rate bond maturing in 2017"). Specials are often motivated by the desire to sell short a specific security in order to arbitrage the yield curve or manage dealer inventory (Duffie, 1996). In contrast, the GC repos are loans, typically short-term, whose collateral belongs to a certain predetermined list (e.g., "Italian government bonds"). The cash lender agrees to take any security from this list as collateral and is thus not looking to sell short a particular one.

Not all repo transactions use a CCP. The repo market has several segments (Copeland et al, 2012): OTC bilateral, tri-party repos, and CCP-cleared. On the OTC market, both parties bear the counterparty risk and set the haircuts. Tri-party repos are transactions in which a private bank organizes the settlement of the operations, but does not bear the counterparty risk. CCP-cleared repos are transactions in which – besides offering settlement services – a clearinghouse bears the counterparty risk and therefore sets the haircut centrally. The CCP inserts itself between the two counterparties: It borrows the security (and lends cash against it) from the cash-borrower, and lends the security to the cash-lender (and borrows cash in exchange). CCP clearing often comes with electronic trading services. Historically, the repo market was an OTC market intermediated by broker-dealers. Over time, electronic trading platforms that match lenders and borrowers anonymously became to dominate the market in the Eurozone. The use of these platforms often comes with attached CCP services. Our data come from such platforms [5].

1.2.2 Data

Transaction data

Our data come from two large electronic platforms (ICAP BrokerTec and MTS repo) and cover the period from January 1st, 2008 to June 30, 2012. ICAP BrokerTec provides us with the bulk of the data, but these do not cover repos based on Italian government collateral. For Italian GC, we rely on data from MTS Repo, which is that country's main electronic repo platform. For both platforms, our raw data contains all repo transactions. For each transaction, data contain (1) whether the transaction is GC or special, (2) the nature of the underlying collateral (say, German government debt), (3) whether the transaction is CCP-cleared or not, (4) the date of the repo transaction and its maturity, and (5) the interest rate and the amount.

We restrict our analysis to GC repo transactions that use sovereign bonds from Eurozone countries as collateral. In these transactions, the lender is allowed to provide any collateral from the GC list, which is considered to be safe enough to warrant cash lending at the repo rate. The GC list is country-specific. As shown in Fig. 1, MTS and ICAP GC repos represent a daily volume of about €50bn during the period, vs. a total daily repo volume of roughly €220bn.

Since our focus is on the role of CCPs, we restrict the sample to CCP-cleared transactions for the most part. Sometimes counterparties sign bilateral contracts rather than going through CCPs, but

[5] The segmentation and motivation for repos are not the same in the US and Europe. The two markets are of similar size, although it is difficult to make accurate comparisons due to the presence of bilateral and triparty segments. As of May 2012, the US repo market is estimated to be $3.04 trillion (Copeland et al, 2012), while the Eurozone repo market is estimated to be €5.6 trillion as of June 2012 (based on a survey of 62 large banks by ICMA, 2013). These measures are subject to double-counting but they suggest comparable sizes. However, the US is dominated by tri-party repos, which account for 53% of the market as of May 2012. In contrast in the EU, CCP-cleared repos account for 55% of the total in 2012 (2012 ECB Money Market Study). Another important difference is that European banks (which hold more government bonds) are very active in European repo markets (Mancini, Ranaldo, and Wrampelmeyer, 2015), while the US repo market is mostly used to finance the shadow banking system (Krishnamurthy, Nagel, and Orlov, 2014). The European repo market is also where the ECB tends to conduct its routine monetary policy operations (see for instance Cassola, Hortaçsu and Kastl, 2013).

this is not the norm. Most of the time, electronic transactions are CCP-cleared. Counterparties trading through ICAP need to clear transactions through LCH.Clearnet Ltd[6]. Counterparties trading Italian GC through MTS have to use Cassa di Compensazione e Garanzia SpA (CC&G). The fact that Italian GC is cleared via a different CCP in our data does not have a bearing on our findings: Our main results are not affected when we exclude Italy. We can distinguish CCP-based vs. bilateral transactions in the ICAP database. We can do the same in the MTS data but only in 2010-2012 (MTS does not allow this distinction in 2008-2009). Assuming that all pre-2010 Italian repo transactions are CCP-based, we find that 85% (80%) of the transactions turn out to be CCP-cleared in our data over the entire period (in the post-2009 period)[7]. We focus on these transactions for our main results (in Section 4), but we return to the CCP/bilateral distinction in additional tests (in Section 5).

In terms of maturity, we restrict our analysis to one-day repo transactions, which represent about 97% of total volume in our data[8]. These one-day transactions are denoted as "overnight", "tomorrow next" and "spot next" depending on the day of delivery.

We collapse these repo trade data into daily observations of GC rates per sovereign collateral. We have GC trades for 11 countries: 5 GIIPS countries (Greece, Ireland, Italy, Portugal, and Spain), and 6 non-GIIPS countries (Austria, Belgium, Finland, France, Germany, and the Netherlands). For each day and each country, we compute two variables. The daily country-level repo rate is the volume-weighted average interest rate on one-day, CCP-cleared, repo transactions. The GC volume is the total value of all transactions for a given country. We ignore daily observations with missing repo rates, except in the tests of Section 4.3, in which we analyze repo volume after assigning a volume of 0 to days with missing repo rates. Table 1 reports summary statistics for repo rates and volume for the entire sample period (January 2008 to June 2012) and for the four subperiods that we consider in our tests: "Normal times" (January 2008 to Lehman Brothers' bankruptcy

[6]One exception is French GC that is cleared via LCH.Clearnet SA, which is an affiliate of LCH.Clearnet Ltd

[7]This assumption seems reasonable given the increasing predominance of CCP-based transactions over bilateral ones, but it inevitably makes our data noisier. To ensure that this does not affect our results, we present our main results excluding Italy in a robustness test (in Appendix Table 1, Panel B). Doing so does not affect our conclusions.

[8]There are no maintenance margins for one-day repos, for which only the initial haircuts matter. Moreover, in one-day repos the uncertainty regarding default premium of the underlying sovereign bond is also reduced to a minimum (compared to, say, one- or three-month repos).

on September 15, 2008); "Sovereign stress times" (January 2009 to December 2010); "Sovereign crisis times" (January 2011 to the day before the 36-month LTRO on December 20, 2011); and "post-LTRO period" (January to June 2012).

Fig. 2 presents the evolution of total daily volumes (averaged by month) of repo transactions broken down by GIIPS and non-GIIPS countries. The average daily volumes have the same order of magnitude, but the volume of GIIPS repos goes down from about €35bn in 2008-2009 to about 20bn in June 2012. Non-GIIPS repo volumes are stable at around €20bn[9]. For Greece, Ireland and Portugal, which enter a bailout program during our sample period, we exclude all observations in and after the month of the bailout program.

Sovereign and bank risk data

We match our repo data with each country's daily credit default swap (CDS) rates from Datastream using the five-year senior CDS series (*Sovereign CDS* in our tables). We also estimate default risk for banks in a given country using the simple average of (five-year) individual bank senior CDS rates to the extent they are available in Datastream. We report summary statistics on bank and sovereign CDS spreads per subperiod in Table 1.

1.2.3 The unfolding of the Euro crisis in our sample

This section provides a short description of the data and preliminary evidence that the repo market was affected by the developments of the European sovereign crisis, despite the fact that the segment we consider is backed by a CCP that is supposed to insulate market participants from default risks. This observation, further refined later, constitutes our main finding.

[9] Appendix Fig. A1 provides a more detailed breakdown by country. Note that each panel uses a different scale. Panel A of Appendix Fig. A1 reports trading volume for Italy, France and Germany, whose total repo trading volume is about €30bn per day. In Panel B, which reports numbers for Austria, Belgium, Spain, Finland and the Netherlands, the trading volume is smaller but never zero (approximately €1bn per day on average, with peaks at about €4bn to €6bn for Belgium, Spain and the Netherlands). Panel C shows volume for the three countries that eventually went through a bailout program (Greece in March 2010, Ireland in November 2010, and Portugal in April 2011), and whose repo markets shut down entirely once their banks obtain financial assistance.

We report in Fig. 3 the repo rates of GIIPS and non-GIIPS transactions over the period that we study (2008-mid 2012), as well as the ECB rate corridor (the deposit rate, which is the lower bound, and the lending facility rate, which is the upper bound). In normal times, the repo rate follows the main ECB policy rate[10]. After October 2008, the ECB greatly expands the size of its interventions (auctions change from partial to full allotment), so that the repo rate converges quickly to the ECB deposit rate. In mid-2010, the Greek sovereign crisis becomes more acute, and all repo rates increase again, up to 50bp above the central bank's deposit rate although the ECB does not scale down the size of its MROs. In the summer of 2011, the sovereign crisis spreads to Italy and Spain, and the repo market separates into two: GIIPS repos remain about 50bp higher than the deposit rate, while non-GIIPS repos fall. This situation lasts for about half a year, until the two rates become realigned with the lower bound of the corridor at the end of 2011 (we argue in Section 4 that the timing coincides with the implementation of the 36-month LTRO of December 2011).

Over the entire period, the average repo rate is not stationary (the Dickey-Fuller test fails to reject the unit root hypothesis at 89%). We deal with the non-stationary series using two approaches. First, our focus on four separate subperiods (2008-Lehman, 2009-2010, 2011, 2012S1) helps. During each of these subperiods except the first one (which is not the focus of our paper), Dickey-Fuller statistics clearly reject the unit root hypothesis, and the time series show no statistically significant trend. Second, in all our specifications we use the difference between the repo rate and the ECB deposit rate. This difference is theoretically motivated (see the next section), and is stationary both within each subperiod and over the entire period.

Fig. 4 displays the evolution of average sovereign CDS spreads of GIIPS and non-GIIPS countries. Similar to repo rates' evolution, CDS spreads for the two groups of countries move very closely until the Greek crisis erupts in early 2010. The two groups start to drift apart but the difference remains moderate until the spring of 2011 (when Portugal officially requires EU assistance to fund its sovereign borrowing). Between mid-2011 and the end of 2011, GIIPS CDS spreads increase from

[10] This is because the ECB's interventions (called Main Refinancing Operations, or MROs for short) are auctions with partial allotment whose goal was to align the repo rate with the main policy rate (see Cassola, Hortaçsu, and Kastl, 2013, for a description).

5 to 25%, while non-GIIPS CDS remain essentially flat. The divergence in CDS rates coincides with the divergence in repo rates during this period.

The above observations suggest a correlation between CDS spreads and repo rates, at least in GIIPS countries. This is surprising, given that all transactions that we consider are CCP-cleared and therefore in principle insulated from default risks. Before we investigate this more deeply, we note that this finding is not present in the aggregate data, which justifies our analysis at the country-level. The time-series relationship between repo rates and sovereign risk is actually negative and statistically significant (in particular in 2009 and 2011) [11]. Hence, aggregate repo rates do not seem to react to sovereign stress. If anything, they react negatively, i.e., repo borrowing becomes cheaper in times of stress. This happens because the aggregate repo rate in our data mixes GC rates on GIIPS and non-GIIPS countries.

Subsequently, we exploit the country-by-country variation to refine our tests. In fact, we find a sharp contrast between the reactions of repo markets to the Eurozone sovereign crisis in GIIPS vs. non-GIIPS countries. Our conceptual framework suggests a channel that is consistent with these results: during periods of significant sovereign stress, the probability of CCP insolvency (conditional on sovereign and member banks defaults) increases.

1.3 Explaining repo rates: A conceptual framework

1.3.1 Assumptions

To analyze the pricing of repo loans, we start from a stylized risk-neutral no-arbitrage model. Assume that cash lenders arbitrage between overnight lending on the repo market at r^{REPO} and lending with no risk to the ECB at the deposit rate r^{ECB}. Repo lending of $P(1-h)$ €is collateralized with P€of sovereign bonds, where h is the haircut and P the price of the bond. The sovereign bond

[11] Appendix Fig. A2 shows how the average repo rate and the average CDS spread correlate. First, we take the difference between the repo rate and the ECB deposit rate to make the series stationary. Then, we compute the average sovereign CDS spread and the average adjusted repo rate, each day, across all 11 countries in our sample. We obtain a time series of 1,149 daily observations, which we plot in Appendix Fig. A2.

defaults with probability π ,in which case the bondholder incurs a loss given default (LGD) of x, which is a random variable with c.d.f. F.

In the data, repo rates and collateral risk are strongly related in times of crisis. For such a link to arise, we need to assume that the cash lender is exposed to the collateral in some states of nature, which necessarily happen when the CCP defaults. To see this, imagine that the CCP never defaults. In this case, repo lending is always safe and at equilibrium $r^{REPO} = r^{ECB}$. Such a model cannot explain the repo rate-to-sovereign CDS spread sensitivity that we document in Section 4. By contrast, if the cash lender becomes exposed to the collateral upon CCP default, then she will price this exposure and the repo rate will be sensitive to collateral risk.

To rationalize the results, we thus need to make the following assumption:

Assumption 1. In case of CCP failure, the lender owns the collateral.

During the period of our study (2008-2012S1) liquidation in case of CCP failure is not very well defined, but the practitioner literature as well as informal interviews with CCP employees, suggest that this is a credible assumption. We defer the discussion on the plausibility of this assumption to Section 3.3.

1.3.2 Set-up

In the absence of sovereign default, the lender is made whole as long as daily fluctuations of the bond price are below the haircut. We assume, accordingly, that the haircut policy is set conservatively enough to absorb such price movements. However, in the alternative scenario, conditional on sovereign default, the expected LGD on $1/(1-h)$ €of bond is thus $\int_h^1 (x-h)dF(x)/(1-h) = G(h)$. G(.) is a decreasing function of h: bigger haircuts allow to minimize the loss in case of default.

Denote p the probability of CCP member default conditional on sovereign default. "CCP member default" is a general term that means the default of one or several banks that trade through the CCP and that are big enough to require a large-scale intervention by the CCP to settle their transactions, which can ultimately cause the failure of the CCP itself[12]. This probability p can be estimated for instance by regressing bank CDS spreads on sovereign CDS spreads as in Acharya, Dreschler and Schnabl (2014), something we also do in Table 7. Finally, we denote λ the probability that the CCP defaults, conditional on both CCP members and sovereign defaults. As in Krishnamurthy, Nagel, and Vissing-Jorgensen (2013), we rely on risk-neutral probabilities rather than the true physical probabilities of default.

Because lenders always have the choice to lend to the ECB at the deposit rate, a no-arbitrage condition implies:

$$r^{ECB} = (1 - p\lambda\pi)r^{REPO} - p\lambda\pi G(h) \tag{1.1}$$

which, after straightforward manipulation and first order approximation, leads to:

$$r^{REPO} = r^{ECB} + (p\lambda G(h)/G(0)).(\pi G(0)) \tag{1.2}$$

This simple framework allows us to interpret the results of our regressions, in which we regress the repo rate on sovereign CDS spread. The sovereign CDS spread measures $\pi G(0)$, i.e., the probability of default π times the expected loss given defaultfor €1 of bond. As a result, our regressions allow us to obtain an estimate of $p\lambda G(h)/G(0)$, which measures the conditional probabilities of default of the CCP and its member banks, as well as the LGD given the haircut. This will be our main empirical strategy.

[12] Modeling the conditional failure of member banks is not necessary since these do not directly affect the cash lender, as counterparty failure would in a bilateral transaction. However, considering the failure of CCP members permits us to describe more realistically the chain of events leading to the failure of the CCP - from sovereign default to member defaults to CCP default. Moreover, it also allows us to motivate the tests of Section 5, in which we consider separately the change in bank risk and the change in perceived CCP risk as possible factors driving the strong link between sovereign CDS spreads and repo rates in 2011.

Finally, note that our framework only allows us to measure the market's perception. The repo rate to CDS sensitivity may increase because market participants become more risk averse. It may also increase because traders hold excessive beliefs that the CCP may fail. Thus, we cannot discard "behavioral" explanations, although we cannot prove them either. It is important to bear in mind, however, that λ is a conditional probability. It is closer to a correlation (between CCP failure and sovereign default) than to the unconditional belief that the CCP will fail.

1.3.3 What happens in case of CCP failure?

We discuss here our Assumption 1 that, in case of CCP default, the lender becomes the owner of the collateral. First, notice that CCP failure is a plausible event. When one or several members default, CCPs typically have buffers that consist of default funds and capital reserves (equity). As long as these buffers are sufficient, non-defaulting members face no loss on their margin accounts. Such events correspond to CCP "non-failure" in the model, since lenders get repaid fully. But in case of a major crisis, these buffers quickly become too small. For instance, as of December 2011, LCH.Clearnet (which clears all non-Italian repos in our data) only had a single default fund, of approximately €680m, for all its clearinghouse activities (both repo and derivatives). This is to be compared with an average daily volume of €17bn on the repo market in our data, excluding Italy. Default on 8% of these transactions with a 50% loss given default would be sufficient to wipe out the entire default fund[13]. Given European banks' active reliance on repo funding, the default of two medium-sized members concurrent with the default of their related sovereign is a shock big enough to exhaust the default fund of LCH.Clearnet[14].

[13] A similar order of magnitude is valid for CCG, the CCP clearing Italian repos in our data. At the end of 2011, CCG had a default fund for bonds of 1.1bn. With an average daily volume of Italian repo of 26bn,defaults on about 9% of the transactions along with 50% haircuts on collateral would be enough to exhaust the default fund.

[14] The recent stress tests conducted by the European Securities Market Association (ESMA) for 17 European CCPs (including LCH.Clearnet Ltd. and CCG) indicate that "... the prefunded resources of CCPs would be sufficient for the reporting dates to cover the losses resulting from the considered historical/hypothetical market stress scenarios after the default of the top-2 EU-wide groups, selected either on the basis of the largest aggregate exposure or also after weighting by their probability of default" (ESMA, 29 April 2016, p.57). However, these stress tests, based on 2014 data and prefunded resource-levels of CCPs, are unlikely to be representative of the weaker conditions of CCPs prior to 2012. In fact, upon request of their regulators, many CCPs had to strengthen their abilities to absorb potential losses. For example, "... in August [2012], LCH.Clearnet Ltd (LCH) established a new ring-fenced default fund of approximately £500 million in respect of its clearing of repo transactions" and introduced new waterfall arrangement for repo clearing (Financial Stability Report, November 2012, pp.13-14)

Second, in case of CCP default, lenders get a fraction of the value of their collateral. This is called "end of waterfall loss sharing". This procedure was not precisely defined in 2011. The Bank of England in 2011 acknowledged that "CCPs do not generally have formal arrangements for allocating losses that exceed their default resources [...] If a CCP were to fail, residual losses would fall on participants (as creditors) and it is likely any allocation would occur in a way that was difficult to predict with certainty and could take a considerable period of time." (Financial Stability Report, December 2011, p.53). After 2011, however, end-of-waterfall loss sharing was codified more explicitly. When default funds are insufficient to absorb all losses, the remaining contracts are "torn up" (see for instance Table A.1. in Elliott, 2013). Then, a haircut is applied to all positions. This haircut reflects the mismatch between positive and negative positions due to the default of some members. It is also a function of the value of the underlying collateral of each lender. Lenders with worse collateral receive a smaller fraction of their claim, which is the spirit of VMGH for derivatives (see Eliott, 2013 or Duffie, 2015). This makes the payoff of lenders sensitive to the value of the collateral in case of default. This allocation rule was confirmed to us by a risk manager at LCH.Clearnet.

Finally, our assumption that the cash lender becomes exposed to collateral in the event of CCP default can be understood as representing the beliefs of market participants about the resolution procedure, rather than the procedure itself. Although end-of-waterfall loss sharing rules were not precisely codified in 2011, it seems reasonable to assume that market participants were behaving as if lenders would be exposed to the collateral in case of CCP default, as it is the case today. In several informal conversations that we had repo traders indicated that they were subject to sovereign exposure limits set by their institutions' risk management departments (for instance, "not more than €500m of Italian paper"). Such anecdotal evidence suggests that risk managers of, at least, several large repo dealers, thought that lending cash against a particular sovereign collateral exposed the bank to this country's debt, which is consistent with our Assumption 1.

1.4 Main results

1.4.1 Sovereign default risk and repo rates

We estimate Eq. (2) by running the following regression, for country c, at date t:

$$r^{REPO}c,t\text{–}r^{ECB}t = \beta SovereignCDS_{c,t} + \delta_c + \delta_t + \epsilon_{c,t} \tag{1.3}$$

where the dependent variable is the spread between the repo rate of country c and the ECB deposit rate, which is our measure of the safe rate of return. The coefficient of interest is β, the sensitivity of the repo rate to the sovereign CDS spread. Our null hypothesis is that $\beta = 0$, i.e. that haircuts are conservative enough, and/or that the CCP and its members are resilient enough. In our baseline specification, the regression also includes country fixed-effects (δ_c) and time fixed effects (δ_t) to account for movements in the common factors affecting the European repo market. We cluster error terms $\epsilon_{c,t}$ at the daily level across countries. Finally, note that the average excess repo rate (the average of r^{REPO}c,t – r^{ECB}t across countries) is a stationary variable, in particular if we focus on the post-Lehman period. The Dickey-Fuller (DF) statistic over the entire period is -2.9, which allows us to reject the unit root hypothesis at the 4%-level[15].

Estimates of Eq.(3) appear in Panels A and B of Table 2, for various subperiods. In Panel B, we report regressions in which δ_c is replaced with country-month fixed effects $\delta_{c,m}$. This forces identification on daily variations within the month. We split our sample into the four subperiods described in Section 2.3: "Normal times", "sovereign stress times", "sovereign crisis times", and "post-LTRO period". The only period in which β is significantly positive in both panels A and B is "sovereign stress times". Before 2011, markets did not seem to price a risk of CCP and member bank default. In 2012, the stress that had built up in the repo market abated. But in 2011, the

[15]If we focus on 2009-2012S1, the DF statistic becomes -4.8, which rejects the unit root hypothesis at less than 0.01%. As we discussed in Section 2.3, the monetary policy of the ECB in normal times implies a large difference between the repo rate and the ECB deposit rate, which explains the relative weakness of the DF test over the entire period. This large difference disappears, and the results of the DF test improve, in the period following Lehman's bankruptcy, which is the period the paper mostly focuses on.

coefficient estimate is positive and statistically significant, although weaker when we control for country-month fixed effects. Using estimates from Panel B, we see that during these "sovereign crisis times", a one-standard deviation increase in the CDS spread leads to an average increase of almost 9 basis points ($= 0.076113bp$) for all one-day Eurozone GC-repo rates combined across countries. The effect is thus moderate and, in our most saturated specification, only significant at 5%. However, this finding conceals a large heterogeneity between GIIPS and non-GIIPS countries, to which we now turn.

1.4.2 Sovereign default risk and repo rates in GIIPS vs. non-GIIPS countries

In our framework, the coefficient β corresponds to $p(h)/G(0)$, which contains the joint conditional default of the CCP and member banks, as well as the effect of the haircut. In this section, we investigate whether β is the same in GIIPS and non-GIIPS countries. A difference may arise because haircuts are too low in transactions using riskier GIIPS collateral, i.e., because $G(h)/G(0)$ is larger in GIIPS countries. To test whether the sensitivity of repo rates to sovereign risk differs between GIIPS and non-GIIPS countries, we create an indicator variable named GIIPS, which is equal to one for GIIPS countries, and zero otherwise. Then, we add an interaction term GIIPSSovereign CDS to the version of Eq. (3) that includes country-month fixed-effects ($\delta_{c,m}$). The coefficient on this interaction term measures the extent to which repo rates are differentially sensitive to sovereign CDS spreads across the two country groups.

We report these results in Table 2, Panel C. They suggest that GIIPS countries mostly drive the positive sensitivity of repo rates to CDS spreads. This relation is statistically significantly negative for non-GIIPS countries: in column 1 the coefficient on Sovereign CDS (the non-interacted term) is equal to -0.051 (significant at the 1%-level), which we understand as evidence of flight to quality. An increase in non-GIIPS CDS spreads indicates general stress in bond markets[16]. In this instance, the CDS spreads of GIIPS countries go up even more, which increases the relative attractiveness of safe haven sovereign debt as collateral. Consistent with this and as expected, the coefficient

[16]This is apparent from Fig. 4. Average CDS spreads of GIIPS and non-GIIPS countries co-move strongly. Over the entire period that we study, the correlation between the two series is 0.77. In 2011, the peak of the sovereign crisis, it reaches 0.85.

estimates for the interacted variables *GIIPSSovereign CDS* are positive and statistically significant at 1% in column 1: The statistically significant estimate of 0.066 in column 1 indicates that a one standard deviation (120bp) increase in sovereign CDS spreads for GIIPS countries raises the related repo rates by some 8bp on average. Consistent with results from Panels A and B, this relation becomes more pronounced at the peak of the sovereign crisis, as does the divergence between GIIPS and non-GIIPS countries. In Panel C of Table 2, the coefficients on the two variables Sovereign CDS and *GIIPSSovereign* CDS are insignificant until 2010 (columns 2 and 3). They become strongly significant at the peak of the crisis (in 2011, column 4). Using the estimate of 0.208 for the interaction term in 2011, a one-standard deviation increase in the sovereign CDS spread of GIIPS countries (120bp) is associated with a 0.208120=25bp relative increase in the GC repo rate of these countries. And consistent with our previous findings, this relation between underlying sovereign-debt risk and GC repo rates decreases after the introduction of the first 36-month LTRO in December 2011: in column 5 of Panel C the coefficient for the interaction is statistically insignificant.

We implement here two robustness checks. First, we rule out the possibility that our results are somehow linked to the maturity mismatch between overnight repo rates and the five-year sovereign CDS[17]. When we replace the latter with the one-year sovereign CDS rates (the shortest sovereign CDS maturity available to us), we obtain very similar results (which we report in Appendix Table A1, Panel A). Second, we explore whether our results are CCP-dependent, and find that they are not. As we explain above, Italian GC repo transactions are cleared by CCG, while all other repos are traded via ICAP and cleared via LCH.Clearnet. To investigate the possibility that only CCG, and not LCH.Clearnet, is considered at risk by the market, we repeat the same regressions excluding Italian transactions and report them in Appendix Table A1, Panel B. We find that our results are not materially affected.

[17] See Augustin (2013) on the term structure of CDS spreads.

1.4.3 Repo volume and sovereign risk

In this section, we ask whether sovereign risk affects trading volume on the repo market. To do this, we run variants of Eq. (3), in which the dependent variable is now the daily volume traded instead of the repo rate. We take the logarithm of 1+volume, and we attribute a volume of 0 to days with no transactions. Our results are not sensitive to this convention, and carry through when we exclude days with missing observations instead. Regression results are reported in Table 3, which is structured exactly like Table 2 (Country and month fixed effects in Panel A, country-month FE in Panel B, GIIPS/non GIIPS interaction in Panel C).

Table 3 shows that the effects we observed for repo rates become somewhat weaker when we look at volume. Panel A shows a strong negative relationship between CDS spreads and repo volume over the entire period, but also in most subperiods and not just the "sovereign crisis time" period. Panel B shows that all these effects are driven by low (monthly) frequency movements in country-level factors. Once we include country-month dummies, the average effect becomes statistically insignificant in all periods, including 2011. We notice, however, that the coefficient is not driven to zero, it only becomes more noisily estimated. Panel C does not show strong evidence that the sensitivity of repo volume to sovereign CDS spreads is stronger for GIIPS countries, as it was very strongly the case for repo rates.

1.5 The transmission channel between sovereign CDS spreads and repo rates

Our next objective is to understand how shocks to GIIPS CDS spreads are transmitted to repo rates. To do this, we use the model of Section 3. If we take Eq. (2) literally, the sensitivity of repo rates to CDS spreads should be equal to $p(h)/G(0)$. It means that sovereign stress transmits to repo rates more when (1) haircuts are set less conservatively, (2) the conditional probability of CCP member failure increases or, (3) the conditional probability of CCP failure increases. Here, we investigate the relative importance of these determinants one by one.

1.5.1 Haircuts

A conservative haircut policy has the potential to eliminate, or at least attenuate, the effect of stress on repo rates. However big the increase in default probabilities of the CCP or some of its members, a high enough haircut h leads to a negligible conditional loss given default G(h), thereby breaking the link between sovereign CDS spreads and repo rates. The findings above show that this link is present in 2011, indicating that haircuts were not generally high enough at that time. To investigate the effect of haircuts on repo rates, we focus on three instances in which haircuts were increased sharply, and ask whether the repo rate-to-CDS sensitivity was affected by these changes in haircuts. Clearly, haircut modifications are themselves endogenous and are adjusted in response to heightened sovereign stress. To deal with this concern, we focus on short periods around haircut changes, but we acknowledge this method is imperfect.

From the website of LCH.Clearnet we could find haircut changes for France, Spain and Italy. These are plotted in Fig. 5. These haircuts are averaged across maturity groups (below and above 7 years). We focus on three episodes in which LCH.Clearnet raises haircuts by more than 100bp. The first two haircut changes occurred for Spain (December 16, 2010 and September 21, 2011), the last one for Italy (November 10, 2011). For the two Spanish haircut changes, we focus on a 3-month window around the haircut change, because the change follows a relatively neat "step function". These two "experiments" correspond to relatively modest haircut rises (slightly above 100bp). The Italian shock of 2011 is bigger: The haircut goes up from approximately 6% to 10%. The problem with this change is that it only lasted a month, after which the haircut went back to 7%. As a result, for the Italian test we thus restrict ourselves to a 1-month window around November 10, 2011.

The results are reported in Table 4. For each shock, we run a variant of Eq. (3) in which we interact all terms with a POST dummy variable equal to one after the haircut change, and zero before. We report the results of these regressions in columns 1, 3 and 5. In this case, the coefficient of interest is the interaction term *POST Sovereign CDS*. We, then, extend the sample to all other countries and add to the specification the HC Country dummy variable, which is equal to one if the country experiences a haircut change (the "treatment" country), and zero otherwise. These regressions are in the spirit of difference-in-difference tests: They allow us to compare the change in repo-to-CDS spread sensitivity in treated countries relative to other Eurozone countries around the haircut change. The coefficient of interest in these regressions is the triple interaction *POST HC Country Sovereign CDS*. These regressions appear in columns 2, 4 and 6 of Table 4.

Overall, the results are consistent with haircuts being effective in "normal times", but not in the second half of 2011, the peak of the sovereign crisis in Europe. The first Spanish haircut seems to have been effective at reducing stress on the Spanish repo market. In Table 4, column 2, the excess sensitivity of Spanish repo rates to CDS spreads goes down from a statistically positive 0.209 before the haircut change to 0.209-0.236 = -0.027, i.e., close to zero, after the change. By contrast, for the changes occurring in 2011, the sensitivity increases strongly after the haircut increase, which we interpret as evidence that the haircut increase was not large enough to insulate the repo market from sovereign stress. In both the Italian and the Spanish cases, the repo rate-to-CDS spread sensitivity actually increased after the haircut increase (columns 3-6).

1.5.2 CCP members risk

When CCP member risk (p in our model) goes up, we also expect the repo-to-CDS sensitivity $p(h)/G(0)$ to increase. In this section, we propose a measure of p and investigate how it changes over time. We show that, if anything, p decreased in 2011, a result coherent with the fact that banks in the Eurozone decreased their exposure to their own sovereigns in 2011 as Angeloni and Wolff (2012) and Acharya and Steffen (2015) show.

To measure p, we regress the average CDS spread of CCP members on the CDS spread of GIIPS countries. Note that p is the probability of default of the average member conditional on sovereign default. As such, it may differ substantially from an unconditional default probability. To estimate it, we exploit Bayes' law and assumptions about stationarity. Let P_t be the unconditional probability that the average CCP member defaults at date t; p is the sovereign default probability; ρ is the probability of member default conditional on GIIPS non-default. According to Bayes' law:

$$P_t = p\pi t + \rho(1 - \pi_t) = (p - \rho)\pi_t + \rho \tag{1.4}$$

where we assume that both conditional member default probabilities p and ρ are stationary. By regressing P_t on π_t, we obtain an estimate of the difference between the two default probabilities $(p - \rho)$, which is a lower bound for p.

Relying on this insight, we estimate $(p - \rho)$ using data on CDS spreads to measure CCP member and sovereign default conditional probabilities. In principle, we could estimate one regression Eq. (4) per sovereign, but reporting results would be cumbersome. To simplify presentation, we only run one regression with π_t measuring average GIIPS sovereign default risk[18]. We use the following first-difference version of Eq. (4):

$$\varDelta CDS_t^{members} = \alpha + \beta.\varDelta CDS_t^{GIIPSsov.} + \gamma.F_t + \epsilon_t \tag{1.5}$$

where $\varDelta$ represents daily differences. We use first difference because DF tests cannot reject the possibility that the (undifferenced) series have unit roots, even within the various subperiods that we analyze, while first-differenced variables are stationary. $CDS_t^{GIIPSsov}$ corresponds to the average change in 5-year CDS on all available GIIPS sovereigns on day t. $CDS_t^{members}$ is the average CDS spread of CCP members on day t. We look at three groups of members separately: Members of both LCH.Clearnet and CCG, members of LCH.Clearnet only, and members of CCG. We obtain the current list of members from LCH.Clearnet and CCG from their websites[19]. Finally, F_t is a risk factor for the CDS market, designed to capture fluctuations in spreads that do not come

[18] As we have seen earlier, repo rates respond more to the CDS spreads of sovereign bonds from GIIPS countries, therefore we focus on CDS spreads of these sovereigns only. Considering average CDS spreads of all countries in the sample yields the same results.

[19] The full list of CCG's members is available at: http://www.lseg.com/post-trade-services/ccp-services/ccg/membership/members. The list of LCH.Clearnet's members is available at: http://www.lchclearnet.com/fr/members-clients/members/current-membership. Pulling these information from the current website may expose us to some form of look ahead bias, although it is not entirely clear how it affects our results.

from Eq. (4). To construct this factor, we follow Pan and Singleton (2008) and compute the first principal component of CDS changes of 5 large European sovereigns (Belgium, France, Germany, Italy and Spain) that are chosen because their CDS spreads are continuously available over the entire period. The resulting factor loads positively on all five sovereigns. We experimented with alternative measures of the risk factor, without a material change in our results[20].

Table 5 reports the results. In Panel A, the dependent variable is the average CDS spread of members of CCG and LCH.Clearnet, the two CCPs clearing trades on the MTS and ICAP platforms, respectively. In panels B and C, we estimate the average default probabilities of LCH.Clearnet and CCG members separately. This split is warranted by the fact that members of CCG are mostly Italian banks and therefore particularly vulnerable to their sovereign CDS. Looking at all panels, we reach the same conclusion: during the sovereign crisis, the probability of member default conditional on GIIPS default does not seem to increase much. If anything, it decreases. This evolution is consistent with the findings of earlier papers, which show that banks in GIIPS countries reduced exposure to their own sovereigns in 2011 (Angeloni and Wolff, 2012; Acharya and Steffen, 2015)[21].

Overall, the evolution of our estimates of CCP member risk p during the crisis does not match the evolution of the repo rate-to-sovereign CDS spread found in earlier tables: Repo stress is the highest in 2011, but this is precisely the moment when member risk p is decreasing. There are two potential explanations for this: (1) market participants' perception that CCP failure risk increased (i.e., λ increased) or (2) haircuts did not increase enough to compensate increased sovereign bond risk (i.e., G(h) increased). Note that in both cases, the probability of CCP failure conditional on sovereign default (λ) has to be non-zero. While it is impossible to discard explanation (2) due to lack of data, we offer below evidence supporting explanation (1).

[20]For instance, we have added the second principal component as an additional control, but it was most of the time insignificant, consistent with the findings of Pan and Singleton (2008). We have also used the average sovereign CDS spread, and a change in the VSTOXX index, which measures the implicit volatility on the EUROSTOXX 50. None of these alternative approaches yield materially different results.

[21]In fact, this reduction in exposure to GIIPS sovereign debt in 2011 is observed for nearly all Eurozone banks (Popov and Van Horen, 2015).

1.5.3 CCP default pricing

This Section discusses the possibility that the increase in repo rates-to-CDS spread sensitivity in 2011 may be explained by an increase in (real or perceived) risk of CCP failure. There is anecdotal evidence that financial regulators and market participants were worried about a large CCP default. For example, Paul Tucker, deputy governor at the Bank of England warned in June 2011 that: "Central counterparties need to adopt prudent collateral policies, but also to monitor the robustness of their clearing members and risks from the business that they are bringing to the CCP. I am not convinced that that is sufficiently recognized by clearing houses or by standard setters" (Financial Times, June 2, 2011). Few months later, he further stated that "There is a big gap in the regimes for CCPs – what happens if they go bust?" (Financial Times, October 24, 2011). The market participants whom we spoke with also indicated that the amount of GIIPS collateral that they could take was severely limited by their risk management, in spite of the risk-protection of the CCP. This is consistent with the view that this protection was considered imperfect at that time.

Note also that the key parameter λ in our model is the probability of CCP default conditional on sovereign default, which is a priori much higher than the unconditional probability. One possible reason is that sovereigns are themselves a possible backstop liquidity provider for CCPs. As discussed in Section 3.3, for instance, the default fund of LCH.Clearnet was not large enough to accommodate the default of more than two average size members in a situation where their collateral would take a 50% haircut. This in itself is an unlikely event, but not conditional on sovereign default.

To test whether market participants perceived CCP risk to be high, we exploit the fact that a non-negligible fraction of the trades on our two platforms are bilateral and therefore not CCP-cleared. Following our equation Eq. (3), we ask whether the repo to CDS sensitivity is lower among CCP-cleared trades. We use data on GC repo bilateral transactions between January 2011 and June 2012 on all non-GIIPS markets, Italy, Portugal and Spain[22]. Bilateral transactions are similar to

[22] Appendix Fig. A3 presents the monthly trading volumes of CCP-based vs. bilateral transactions in our sample. These data exclude Greece and Ireland, as their repo markets shut down before January 2011.

CCP-based ones in that they use the same GC lists and haircuts, but they are not anonymous. Thus, bilateral transactions that go through trading platforms are very similar to OTC transactions. They represent smaller volumes than the CCP-cleared transactions that we focused on previously, but they are still large enough to help us implement our test. In non-GIIPS countries, bilateral trades represent about 15% of CCP-cleared trades and are quite stable over time. In Portugal and Spain, they represent much smaller volumes, in particular in the last four months of 2011, when they virtually disappear.

Because bilateral trades are less frequent than CCP-cleared ones, many days have no transaction data, and therefore no bilateral repo rate. To get around this data limitation, we aggregate the rates at the monthly level, taking the average monthly rate for the two series, and replacing country-month fixed effects by separate country fixed-effects and month fixed-effects[23]. We then repeat the tests of Table 2 separately for CCP-based and bilateral repo rates.

Table 6 reports the results. In column 1 of Panel A, in which the dependent variable is the CCP-cleared repo spread (over and above ECB deposit rate) in year 2011, the coefficient on *Sovereign CD*S is negative but statistically insignificant. The coefficient on *GIIPSSovereign CDS* is statistically significant and, reassuringly, of the same order of magnitude as the corresponding coefficient that we obtain on the same interaction variable in Table 2, Panel C. In column 2, a similar result holds for bilateral rates but the coefficient on *GIIPSSovereign CDS* is smaller than in column 1. This suggests that in 2011 repo rates are not less sensitive to sovereign stress in the CCP-based segment of the market (if anything, the contrary happens). They are, however, in 2012 (Panel B), when the coefficient on *GIIPSSovereign CDS* becomes smaller for CCP-based repo than for bilateral repo, although both coefficients are statistically insignificant. These results have to be interpreted with care because when sovereign stress rises, the pool of banks that have access to the bilateral market may shrink to only the safest ones. Thus, the test on bilateral repo rates probably underestimates their sensitivity to sovereign stress.

[23]Our results are the same if we use daily rates and keep only days with non-zero bilateral trade volume.

1.6 Alternative hypotheses

1.6.1 Market power of lenders

An alternative explanation of our findings is that the second half of 2011 was a period of increased market power of investors willing to lend cash against stressed sovereign collateral. The intuition is that during this phase of intense sovereign stress, most cash-rich banks refused to increase their exposure to GIIPS sovereign risk. At the same time, banks in the periphery had few alternative sources of funding and were thus ready to accept higher rates to be able to continue borrowing from the repo market. As a result, the increase in the repo rates-to-CDS spreads sensitivity that we document could come from a handful of cash-rich banks willing to lend against bonds that few wanted as collateral.

The demand and supply for repo transactions are hard to estimate, but a few elements suggest that shifts in the demand and supply curves on the repo market cannot fully explain our main finding. On the borrowing side, July-December 2011 is a period during which the supply of GIIPS collateral from potentially risky counterparties was going down, not up. Angeloni and Wolff (2012) show that between July and December 2011, holdings of their own sovereign bonds by Italian, Spanish, Irish and Portuguese Banks went down in absolute terms. Acharya and Steffen (2015) document that, over 2011, own-sovereign holdings of GIIPS banks went down by about 3%. If anything, it looks like GIIPS banks had less GIIPS collateral to supply, not more, in the second half of 2011.

On the lending side, we could not find evidence of weaker competition between lenders in 2011S2. Our transactions data do not contain counterparty IDs. As a result, we cannot measure lender concentration directly. But some aggregate data are available, and these do not show evidence of increased concentration on the repo market. We show this evidence in Fig. A4. First, the ECB Money Market Surveys from 2009 to 2014 report annually the percentage of reverse repos accounted for by the top 5, 10 and 20 largest European banks in this market. Over time, the market share of the largest banks did not increase but instead decreased (Appendix Fig. A4, Panel A). Second, we use Bankscope and pull data on reverse-repos from the balance sheets of banks. The evolution of the Herfindahl – Hirschman Index based on this variable suggests that over time, the lending side of the repo market becomes less, not more, concentrated, with no breakdown of this trend in 2011 (Appendix Fig. A4, Panel B). Unfortunately, we cannot observe this concentration separately for each type of sovereign collateral, so we cannot rule out the possibility that the lending side of the repo market became more competitive on some bonds and less competitive on others. However, increased overall competition in this market suggests that arising opportunities should have been arbitraged away more easily in 2011 than in the earlier years in our study.

A way to account for the possibility that banks from GIIPS countries suffered from a liquidity crunch is to add country-level variables that capture this phenomenon in our main specification. This liquidity shortage story posits that banks from GIIPS countries would have difficulty accessing the unsecured interbank market because of higher risk associated with their sovereign or themselves. Thus, their only way to obtain funding is to borrow on the repo market against collateral that cash-rich banks are reluctant to accept, which leads to an increased cost of borrowing. To measure the access of local banks to the unsecured interbank market, we collect data on daily outstanding volume of Certificates of Deposit (CD) at the level of each country in our sample. This variable should take low values when a country's banks have difficulty accessing the unsecured funding market. As an alternative proxy for the liquidity crunch facing European banks we use daily country-level bank CDS spread. This measure should peak when banks are under severe liquidity stress. It is a less precise measure of funding difficulties of banks than the outstanding CD volume, but it allows us to capture more generally situations in which changes GIIPS repo rates are driven by difficulties, including liquidity funding problems, faced by of GIIPS banks.

In Table 7, we repeat our main tests of Table 2 adding a control variable at a time. In Panel A, column 4 the coefficient estimate for the *GIIPS Sovereign CDS* interaction is negative (and statistically significant) as expected: as country-level outstanding CD Volume increases, repo spread decreases in 2011. In Panel B, column 4 the coefficient estimate for the *GIIPS Sovereign CDS* interaction is positive (and statistically significant) as expected: as country-level average bank CDS spread increases, repo spread increases in 2011. Importantly for us, adding these variables does not eliminate the strong relation between sovereign CDS spreads and repo rates in 2011, suggesting that this latter finding is not mostly due to liquidity stress of GIIPS banks.

1.6.2 Haircut policy of the ECB

In this section, we explore the possibility that the ECB's haircut policy may drive our results. The ECB does most of its monetary policy interventions on the repo market, so it has the power to affect repo rates. Conventional monetary policy operations are not country specific, so they should be absorbed in the day fixed effects of our regressions. But since the crisis, the ECB has started to intervene through its collateral list, by changing the haircuts that it takes on specific collateral[24]. It could be the case that the ECB responds to increased sovereign risk by differentially increasing the haircuts it demands on riskier sovereigns. If the CCPs in our data fail to react by aligning their haircuts on the ECB, lending cash against stressed collateral through the CCP becomes less attractive to investors, and rates should increase. Thus, if the ECB increases haircuts on stressed sovereigns, our estimates would be biased upward. If, on the contrary, the ECB reduces haircuts on stressed sovereigns, they are biased downward.

To implement this test, we add the ECB's haircut as an additional control to Eq. (3) and we estimate the following equation:

$$r_{c,t}^{REPO} - r_t^{ECB} = \beta.SovereignCDS_{c,t} + \gamma.ECBHC_{c,t} + \delta_{c,m} + \delta_t + \epsilon_{c,t} \tag{1.6}$$

where $ECBHC_{c,t}$ is the average haircut taken by ECB on sovereign bonds of country c at date t. We compute this measure using the publicly available collateral list of the ECB.11 A natural hypothesis is that $\gamma > 0$: When the ECB increases its haircut on country c, lending to the ECB becomes relatively more attractive (safer), and lending through the platform requires a higher risk premium. If however, $ECBHC_{c,t}$ and $CDS_{c,t}$ are positively correlated, and the haircut is omitted from the equation, the OLS estimate of β is biased upward.

[24] Nyborg (2016) suggests that differential ECB haircuts have effectively subsidized certain sovereigns.

We report estimates of Eq. (6) in Appendix Table A2. We only report results including country-month fixed effects though results without them deliver the same message. In both specifications (with sovereign CDS, or sovereign CDS interacted with the GIIPS dummy), controlling for the haircut of the ECB does not change our results.

1.6.3 Accounting for country-specific risk exposure

In Eq. (3), we control for common factors on the repo market through the inclusion of a day fixed effect. The limitation of this approach is that it assumes that all repo rates have the same exposure to the risk factors. However, it is reasonable to think that some countries have different exposures to the same risk factor. Our main specification partially deals with this issue with country-month fixed effects, but these can only capture slow-moving factors. Given the data available to us, we cannot identify the effect of the sovereign CDS if we introduce country-level day-fixed effects as well. In this section, we adopt a different approach: We focus on a specific risk factor (the Vixx), and allow for different country-specific exposures across country-level repo rates. We do this by estimating the following version of our basic Eq. (3):

$$r_{c,t}^{REPO} - r_t^{ECB} = \beta . SovereignCDS_{c,t} +_c . Vixx_t + \delta_{c,m} + \delta_t + \epsilon_{c,t} \tag{1.7}$$

where $Vixx_t$ is the Vixx obtained at the daily frequency from Datastream. $_c$ captures the country-specific exposure to volatility risk. While there is no clear consensus in the literature about the factor structure of repo rates, we take the Vixx as a first pass measure of “risk aversion” like Mancini, Ranaldo, and Wrampelmeyer (2015).

We run Eq. (7) and report the results in Table A3. We only report results including country-month fixed effects though results without them deliver the same message. In both specifications (with sovereign CDS, or sovereign CDS interacted with the GIIPS dummy), controlling for differential country exposures to Vixx does not change our results.

1.7 Conclusion

We analyze the sensitivity of repo market rates to sovereign default risk during the Eurozone crisis. This sensitivity is very high, even for CCP-cleared repos, in which lenders are in principle protected against default risks. We propose a simple framework that allows us to decompose this sensitivity into (1) CCP default risk, (2) CCP members default risk, and (3) haircut policy effectiveness. In 2009-2010, the sensitivity is low, in spite of significant bank risk. The evidence from a haircut increase experiment in 2010 suggests that CCP haircut policies appear to have been effective at reducing repo stress. Overall, markets behave as if the CCP was able to insulate the repo market from stress in 2009-2010. In 2011, however, attempts at raising haircuts prove ineffective. The repo-to-sovereign risk sensitivity increases strongly, despite the fact that bank default risk decreases somewhat during that period.

Our results are consistent with CCP failure being perceived as a reality and being priced in repo rates. Given how crucial the repo market is for banks, such failure needs to be dealt with through ex ante regulation. Until 2011, explicit resolution frameworks (especially end-of-waterfall loss-sharing rules) were lacking because CCPs were perceived as solid and unlikely to fail. 2011 has proved that this was not the case and central banks began to push much harder for explicit CCP resolution frameworks.

Our analysis may also suggest that central banks have the power to alleviate stress on CCPs through massive intervention. After the December 2011 LTRO announcement by the ECB, repo rates-to-CDS spreads sensitivity went down dramatically, indicating that market participants have stopped to price CCP default risk. There are many possible channels through which this may be the case. For instance, by making large long-term loans to borrowers, the ECB may have made it much less risky for lenders to lend through private CCP-cleared platforms, but this is only one of the channels.

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Figure 1.1: **Average daily trading volume in the Eurozone interbank repo market**

This figure presents the evolution of different segments of the Eurozone interbank repo market between 2008 and 2012. Interbank Secured, Interbank Secured Bilateral and Interbank Secured Bilateral CCP based, Eurex GC Pooling are from Mancini, Ranaldo and Wrampelmeyer (2014). MTS/ICAP GC is the sum of one day GC repo trades in our dataset. All numbers are in bn of average daily volume.

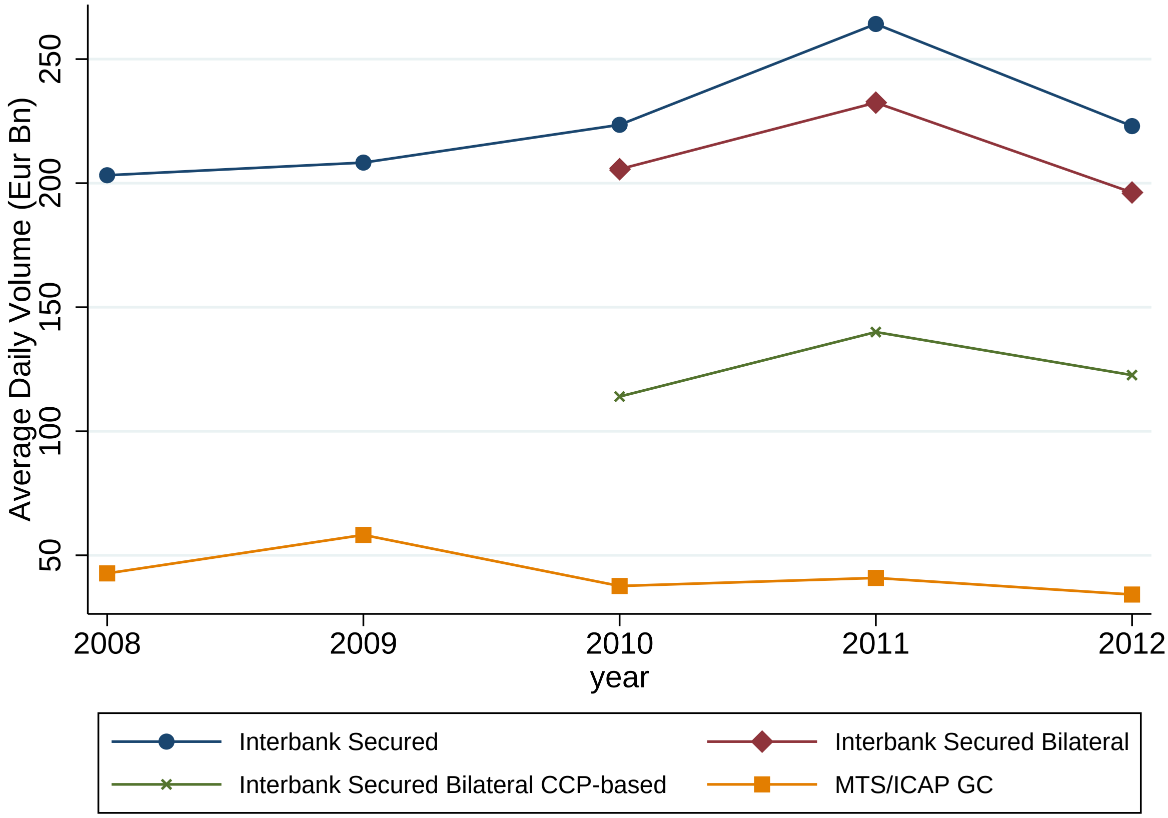


Figure 1.2: **Evolution of the volume of repo transactions in the Eurozone, GIIPS vs Non GIIPS, 2008-2012 S1**

This figure presents the monthly evolution of the average daily volume of General Collateral (GC) repo in the Eurozone between January 2008 and June 2012, for GIIPS countries (Greece, Ireland, Italy, Portugal and Spain) and the six non-GIIPS countries in our sample. The scale of the y-axis is in bn.

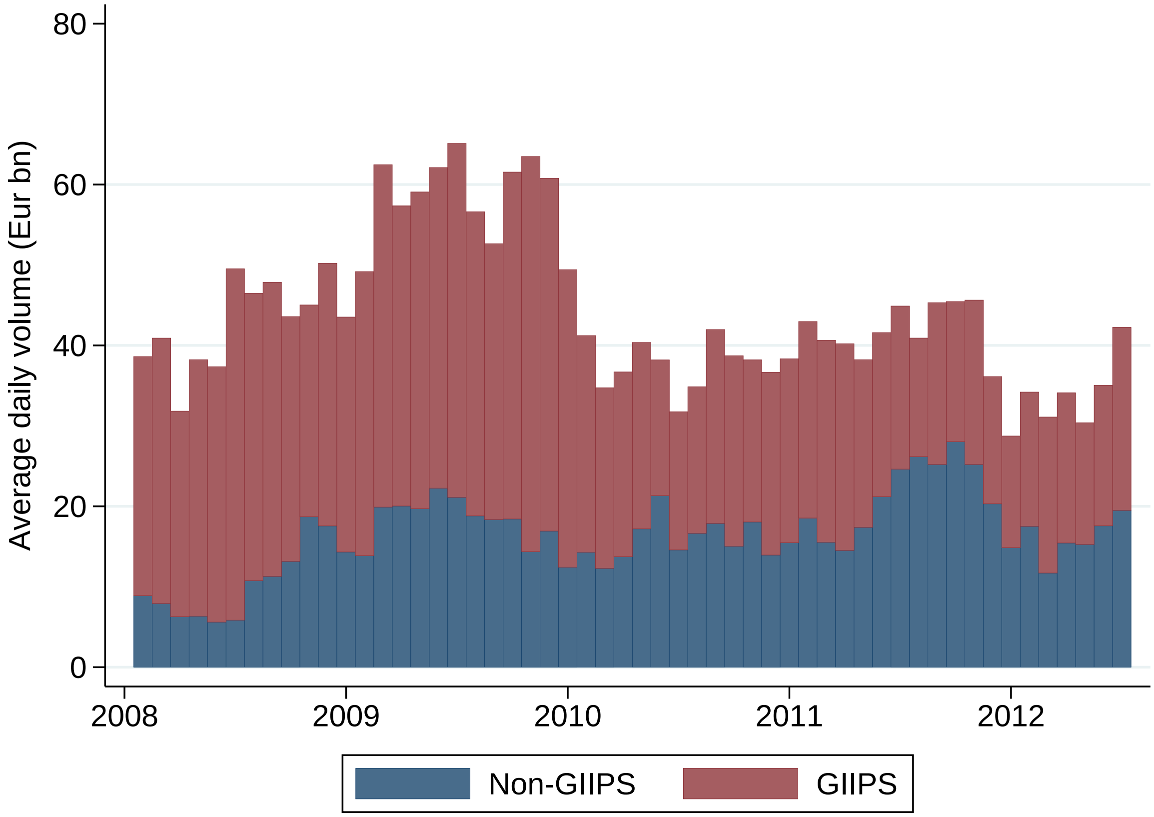


Figure 1.3: **Interest rates, 2008-2012 S1**

This figure presents the evolution of the ECB marginal lending and deposit rates, as well as the average General Collateral (GC) repo rate for GIIPS (Greece, Ireland, Italy, Portugal and Spain) and non-GIIPS Eurozone countries between January 2008 and June 2012. Interest rates are expressed in percent. The vertical red line on the left corresponds to Lehman Bankruptcy of September 15, 2008, whereas the vertical red line on the right corresponds to ECB's 36-month LTRO announcement of December 20, 2011.

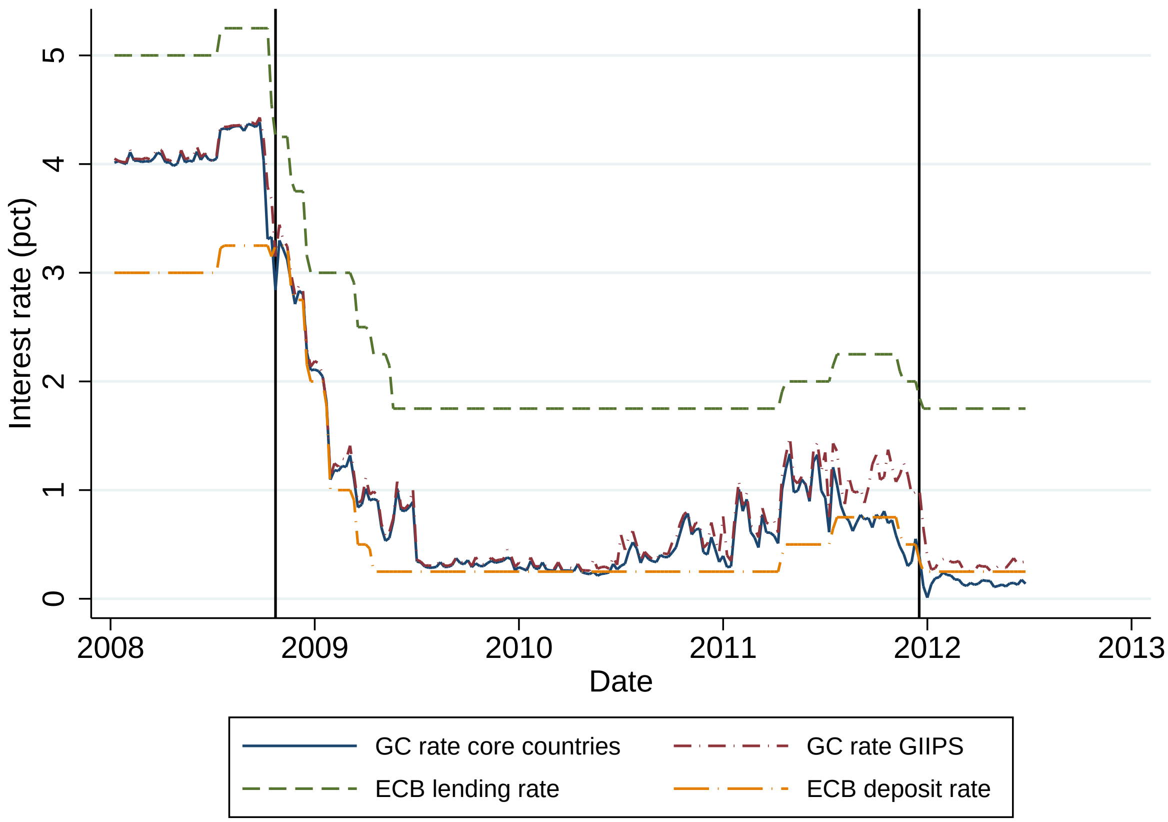


Figure 1.4: **Sovereign CDS spreads, 2008-2012 S1**

This figure presents the evolution of weekly average sovereign CDS spreads for GIIPS (Greece, Ireland, Italy, Portugal and Spain) and non-GIIPS Eurozone countries between January 2008 and June 2012. CDS spreads are in percent. The vertical red line on the left corresponds to Lehman Bankruptcy of September 15, 2008, whereas the vertical red line on the right corresponds to ECB's 36-month LTRO announcement of December 20, 2011.

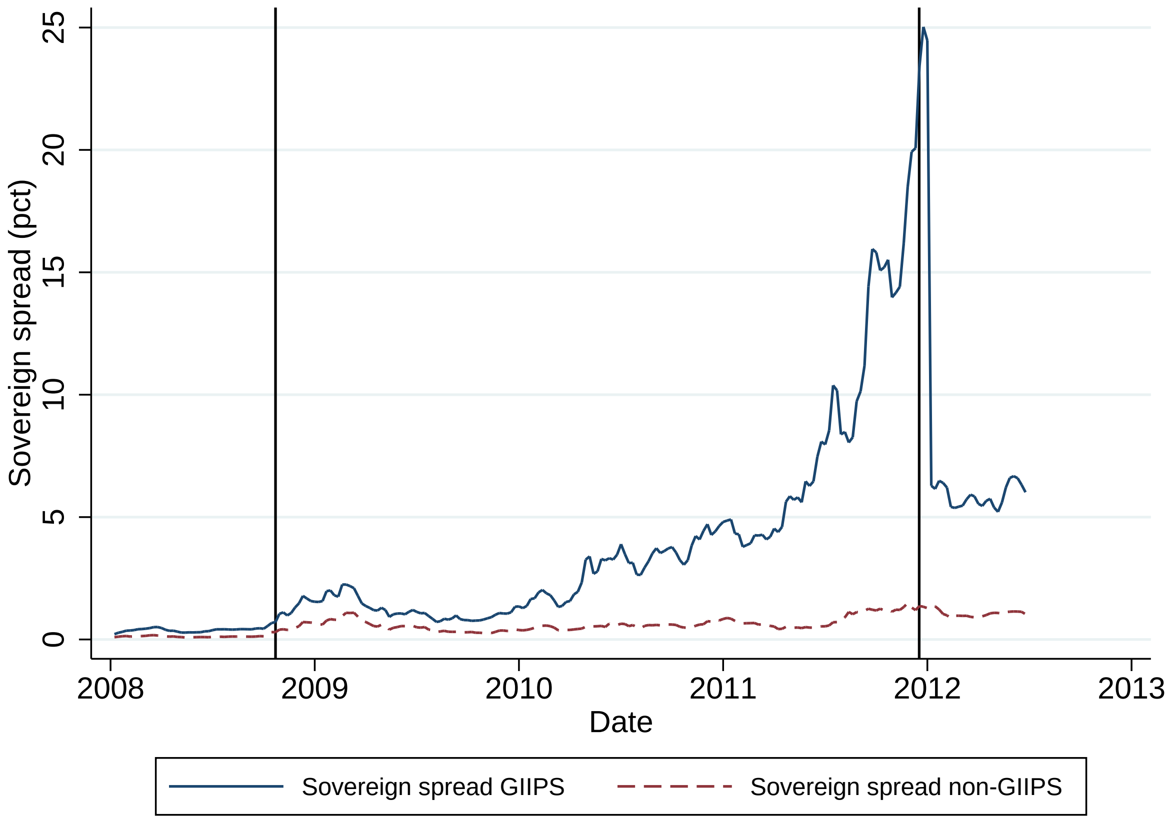


FIGURE 1.5: **The evolution of haircuts**

This figure presents the evolution of haircuts applied to General Collateral (GC) repo transactions by ICAP BrokerTec in France, Italy and Spain between 2008 and June 2012. Haircuts are averaged across maturity groups (below and above 7 years) and are expressed in percent.

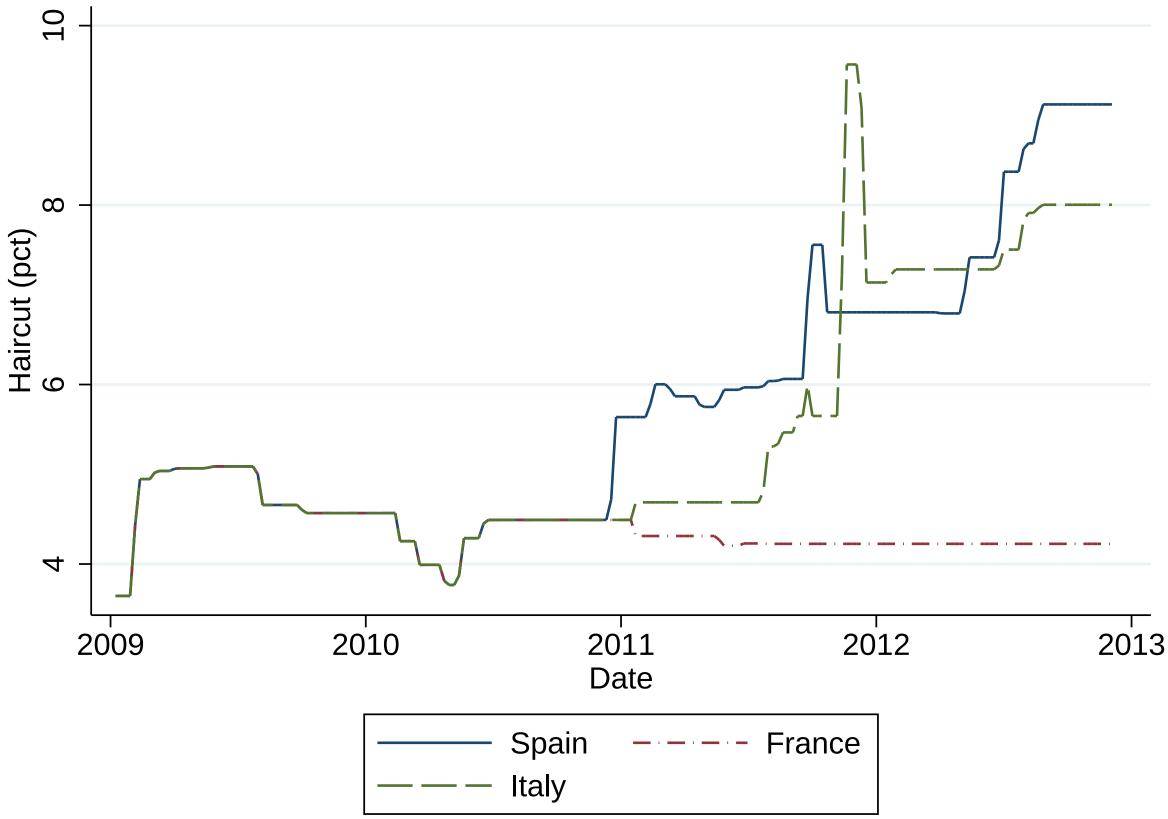


Table 1: Summary Statistics

This table reports summary statistics over the entire sample period, and over each of the four subperiods we consider in subsequent tests. *Repo Rate-ECB Deposit Rate* is the annualized country-level average daily general collateral (GC) repo rate for one-day repo contracts minus the ECB deposit facility rate. *Daily Volume* is the country-level total daily trading volume of such repo contracts. *Sovereign CDS Spread* is the country-level daily 5-year sovereign credit default swap rate. *CCP Member CDS Spread* is the average daily 5-year CDS spread of all financial institutions that are members of the CCPs in the sample. *Local Banks' CDS* is the daily country-level average of 5-year CDS spreads of local banks. *CD Volume* is the daily country-level amount outstanding of Certificates of Deposits of local banks.

	Number of Observations	Mean	Median	Std. Dev.	Min	Max
height**Jan. 2008 to June 2012**						
Repo Rate-ECB Deposit Rate (Pct)	8,814	0.31	0.14	0.40	-0.65	1.88
Daily Volume (Billions Euros)	8,814	5.80	1.65	9.44	0.03	61.77
Sovereign CDS Spread (Pct)	8,471	1.04	0.68	0.95	0.05	5.22
CCP Members CDS Spread (Pct)	8,814	1.78	1.53	1.26	0.35	9.24
Local Banks CDS (Pct)	7,872	1.96	1.53	1.26	0.35	9.24
CD Volume (Billions)	7,667	52.74	9.28	104.37	0.00	373.34
Jan. 2008 to Lehman's bankruptcy						
Repo Rate-ECB Deposit Rate (Pct)	1,218	1.06	1.06	0.06	0.74	1.46
Daily Volume (Billions Euros)	1,218	6.17	1.05	11.62	0.03	53.27
Sovereign CDS Spread (Pct)	989	0.24	0.20	0.15	0.05	0.64
CCP Members CDS Spread (Pct)	1,218	0.89	0.90	0.24	0.46	1.68
Local Banks CDS (Pct)	913	0.82	0.76	0.26	0.35	2.07
CD Volume (Billions)	1,021	63.07	7.85	120.79	0.17	346.09
Jan. 2009 to Dec. 2010						
Repo Rate-ECB Deposit Rate (Pct)	4,190	0.19	0.10	0.21	-0.45	1.63
Daily Volume (Billions Euros)	4,190	5.92	1.17	10.35	0.03	61.77
Sovereign CDS Spread (Pct)	4,134	0.97	0.68	0.76	0.17	4.81
All CCP Members CDS Spread (Pct)	4,190	1.41	1.41	0.35	0.83	2.32
Local Banks CDS (Pct)	3,837	1.73	1.40	1.06	0.56	8.88
CD Volume (Billions)	3,562	49.45	11.12	99.37	0.01	373.34
Jan. 2011 to Dec. 2011 LTRO						
Repo Rate-ECB Deposit Rate (Pct)	1,857	0.30	0.29	0.33	-0.43	1.88
Daily Volume (Billions Euros)	1,857	5.80	3.10	6.78	0.03	38.51
Sovereign CDS Spread (Pct)	1,857	1.36	1.00	1.13	0.23	5.22
All CCP Members CDS Spread (Pct)	1,857	2.60	2.19	0.84	1.53	4.52
Local Banks CDS (Pct)	1,753	2.61	2.22	1.39	1.09	9.24
CD Volume (Billions)	1,692	50.39	8.90	96.99	0.00	323.30
Jan. 2012 to June 2012						
Repo Rate-ECB Deposit Rate (Pct)	882	-0.05	-0.07	0.08	-0.21	0.22
Daily Volume (Billions Euros)	882	4.85	2.30	5.80	0.03	27.18
Sovereign CDS Spread (Pct)	882	1.77	1.22	1.20	0.28	4.73
All CCP Members CDS Spread (Pct)	882	3.25	3.26	0.42	2.55	3.93
Local Banks CDS (Pct)	837	3.23	3.03	0.94	1.83	5.67
CD Volume (Billions)	837	54.78	8.55	104.16	0.20	326.90

Table 2: GC repo rates and sovereign CDS spreads

This table report estimates of fixed-effect panel regressions in which the dependent variable is the daily country-level average general collateral (GC) repurchase agreement rate minus the ECB deposit facility rate (*Repo Rate-ECB Deposit Rate*). The explanatory variables are the daily country-level 5-year sovereign credit default swap rate (*Sovereign CDS*) in panels A and B, and its interaction with an indicator variable equal to one for Greece, Ireland, Italy, Portugal and Spain, and zero otherwise (*GIIPS*), in Panel C. All regressions include day fixed effects. Moreover, Panel A regressions include country fixed effects, and regressions in panels B and C include country-month fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the daily level. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: Fixed-effect regressions

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	0.0650***	-0.0233	0.0158***	0.192***	0.0332***
	(14.54)	(-0.58)	(6.34)	(16.53)	(6.78)
Day FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	No	No	No	No	No
N	8471	989	4174	1817	882
r2	0.959	0.739	0.941	0.922	0.933

Panel B: Fixed-effect regressions with country-month fixed effects

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	0.0145	-0.0997	0.00175	0.0758**	0.00746
	(1.19)	(-1.30)	(0.21)	(2.28)	(0.57)
Day FE	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No
Country Month FE	Yes	Yes	Yes	Yes	Yes
N	8471	989	4174	1817	882
r2	0.980	0.785	0.950	0.949	0.946

Panel C: GIIPS vs. non-GIIPS countries

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	-0.0506***	-0.130	-0.0303	-0.108***	0.0156
	(-2.87)	(-0.58)	(-1.23)	(-3.36)	(1.13)
GIIPS*Sovereign CDS	0.0655***	0.0282	0.0304	0.208***	-0.00885
	(3.43)	(0.15)	(1.32)	(5.24)	(-0.48)
Day FE	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No
Country Month FE	Yes	Yes	Yes	Yes	Yes
N	8471	989	4174	1817	882
r2	0.981	0.785	0.950	0.950	0.946

Table 3: GC repo volume and sovereign CDS spreads

This table reports the estimates of fixed-effect panel regressions in which the dependent variable is the logarithm of the daily country-level general collateral (GC) repurchase agreement volume in bn *(ln(Daily Volume+1))*. The explanatory variables are the daily country-level 5-year sovereign credit default swap rate (*Sovereign CDS*) in panels A and B, and its interaction with an indicator variable equal to one for Greece, Ireland, Italy, Portugal and Spain, and zero otherwise (*GIIPS*), in Panel C. All regressions include day fixed effects. Moreover, Panel A regressions include country fixed effects, and regressions in panels B and C include country-month fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the daily level. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: Fixed-effect regressions

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	-0.368***	-0.160	-0.900***	-0.413***	-0.412***
	(-8.27)	(-0.10)	(-17.42)	(-4.77)	(-3.94)
Date FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	No	No	No	No	No
N	10135	1263	5053	2117	989
r2	0.696	0.817	0.721	0.727	0.816

Panel B: Fixed-effect regressions with country-month fixed effects

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	-0.609***	0.688	0.395**	-2.215***	0.145
	(-7.62)	(0.17)	(2.28)	(-10.14)	(0.52)
GIIPS*Sovereign CDS	0.227***	-0.748	-1.288***	1.682***	-0.583**
	(3.66)	(-0.23)	(-7.73)	(10.65)	(-2.10)
Date FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	No	No	No	No	No
N	10135	1263	5053	2117	989
r2	0.697	0.817	0.724	0.739	0.817

Panel C: GIIPS vs. non-GIIPS countries

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	0.345	-0.645	1.433**	0.128	-0.533
	(1.10)	(-0.09)	(2.34)	(0.31)	(-1.03)
GIIPS*Sovereign CDS	-0.523*	4.396	-1.489**	-0.471	0.0983
	(-1.73)	(0.78)	(-2.53)	(-1.08)	(0.20)
date FE	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No
Country Month FE	Yes	Yes	Yes	Yes	Yes
N	10135	1263	5053	2117	989
r2	0.811	0.851	0.791	0.828	0.849

Table 4: The impact of haircuts on the repo rate-to-CDS spread sensitivity

This table reports the estimates of OLS regressions explaining the daily country-level general collateral (GC) repo rate minus the ECB deposit facility rate (*Repo Rate-ECB Deposit Rate*) around the haircut changes on Spanish repos of December 16, 2010 and September 21, 2011 and around the haircut change on Italian repos of November 10 2011. The explanatory variables are the daily country-level 5-year sovereign credit default swap rate (*Sovereign CDS*), an indicator variable equal to one after the haircut change (*POST*), an indicator variable equal to one for Spain or Italy (*HC COUNTRY*), and interactions between these variables. Columns 1 and 3 present the results for Spanish repo rates only in a 6-month window around the haircut change, respectively for the December 2010 and the September 2011 increases. Column 5 presents the results for Italian repo rates only in a two-month window around the haircut change of November 2011. Columns 2 and 4 present the results for Spanish repo using a difference-in-differences estimation using repo rates from all Eurozone countries as the control group in a 6-month window around the two Spanish haircut changes. Column 6 presents the results for Italian repo using a difference-in-differences estimation using repo rates from all Eurozone countries as the control group in a two-month window around the November 2011 haircut change. In columns 1, 3 and 5, standard errors are corrected using the Newey-West procedure with a 5-day lag. In columns 2, 4 and 6, standard errors are clustered at the daily level. t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

	Spain December haircut change		Spain September 2011 haircut change		Italy November 2011 haircut change	
	(1) Spain Only	(2) Spain and Others	(3) Spain Only	(4) Spain and Others	(5) Italy Only	(6) Italy and Others
Sovereign CDS	-0.0822	-0.291***	-0.385***	-0.245***	-0.095	-0.111
	(-1.47)	(-5.98)	(-3.51)	(-6.24)	(-1.01)	(-1.53)
POST	0.586***	0.068*	-1.501***	-0.340***	-1.289***	-0.095**
	(2.79)	(1.70)	(-3.73)	(-8.48)	(-3.00)	(-2.04)
POST*	-0.209**	0.0271**	0.524***	0.203***	0.357***	0.0587***
Sovereign CDS	(-2.26)	(2.07)	(4.01)	(9.88)		
HC*		0.209***		-0.140		0.016
Sovereign CDS		(4.24)		(-1.05)		(0.16)
POST*		0.518***		-1.161**		-1.172**
HC Country		(2.68)		(-2.32)		(-2.21)
POST*HC Country*		-0.236**		0.320**		0.291**
Sovereign CDS		(-2.58)			(2.06)	(2.22)
Constant	0.524***	0.644***	1.498***	0.580***	0.851**	0.272**
	(4.19)	(11.25)	(4.52)	(6.12)	(2.36)	(2.27)
Ctry FE	No	Yes	No	Yes	No	Yes
N	88	997	111	951	44	333
r2		0.148		0.571		0.803

Table 5: GIIPS sovereign CDS spreads and the CDS spreads of CCP members

This table reports OLS regressions of changes in CCP members' CDS spreads on changes in GIIPS sovereign CDS spreads, controlling for a CDS risk factor. *Change in GIIPS Sovereign CDS* is the average daily change in the spread of the 5-year sovereign CDS across all 5 GIIPS countries. *CDS common risk factor* is the first principal component of the vector of CDS changes of all sovereign CDS. In panel A, the dependent variable is the average change of CDS of LCH.Clearnet and CCG members. In Panel B, we use the average CDS change of LCH.Clearnet members only. In Panel C, we use the average CDS change of CCG members only. t-statistics are presented in parentheses. GIIPS countries are Greece, Ireland, Italy, Portugal and Spain. Standard errors are robust to heteroskedasticity. t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: Delta CDS of all CCP members

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Delta GIIPS Sovereign CDS	0.001	0.796**	0.034**	0.004	0.001
	(0.72)	(2.39)	(2.33)	(0.64)	(0.57)
CDS common risk factor	0.024***	0.083***	0.023***	0.022***	0.028***
	(24.99)	(4.01)	(14.10)	(17.54)	(12.08)
N	1081	136	486	249	125
r2	0.483	0.241	0.597	0.688	0.612

Panel B: Delta CDS of members of LCH.Clearnet

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Delta GIIPS Sovereign CDS	0.001	0.815**	0.034**	0.003	0.0002
	(0.71)	(2.37)	(2.21)	(0.65)	(0.47)
CDS common risk factor	0.024***	0.085***	0.022***	0.021***	0.027***
	(23.22)	(4.10)	(14.01)	(16.48)	(11.69)
N	1081	136	486	249	125
r2	0.461	0.237	0.596	0.681	0.612

Panel C: Delta CDS of members of CCG

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Delta GIIPS Sovereign CDS	0.0005	0.781*	0.020	0.002	0.0005
	(0.29)	(1.98)	(1.29)	(0.20)	(0.89)
CDS common risk factor	0.027***	0.091***	0.023***	0.025***	0.033***
	(28.59)	(3.51)	(12.75)	(19.74)	(13.74)
N	1081	136	486	249	125
r2	0.481	0.219	0.536	0.731	0.621

Table 6: Repo-to-CDS spread sensitivity in CCP-cleared vs. bilateral transactions

This table reports the estimates of fixed-effect panel regressions in which the dependent variable is the monthly country-level volume-weighted average general collateral (GC) repo rate minus the ECB deposit facility rate (*Repo Rate-ECB Deposit Rate*) in column 1 and the monthly country-level volume-weighted average bilateral repo rate minus the ECB deposit facility rate in column 2. The explanatory variables are the volume-weighted average monthly country-level 5-year sovereign credit default swap rate (*Sovereign CDS*), and its interaction with an indicator variable that is equal to one for Portugal, Italy and Spain, and zero otherwise (*GIIPS*). Observations are limited to countries for which both bilateral and GC repo transactions are observed in a given month. The regressions include month fixed effects and country fixed effects. t-statistics are presented in parentheses. Standard errors are robust to heteroskedasticity. t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: 2011

	(1) CCP	(2) BIL.
Sovereign CDS	-0.018	-0.003
	(-0.31)	(-0.05)
GIIPSSovereign CDS	0.186***	0.141**
Month FE	Yes	Yes
Country FE	Yes	Yes
Number of observations	84	84
r2	0.942	0.882

Panel B: 2012

	(1) CCP	(2) BIL.
Sovereign CDS	0.038**	0.019
	(2.86)	(0.50)
GIIPSSovereign CDS	-0.016	0.018
	(-1.12)	(0.54)
Month FE	Yes	Yes
Country FE	Yes	Yes
Number of observations	38	38
r2	0.985	0.944

Table 7: GC repo rates and banks' funding liquidity risk

This table report estimates of fixed-effect panel regressions in which the dependent variable is the daily country-level average general collateral (GC) repurchase agreement rate minus the ECB deposit facility rate (*Repo Rate-ECB Deposit Rate*). The explanatory variables are the daily country-level 5-year sovereign credit default swap rate (*Sovereign CDS*), the GIIPS indicator variable equal to one for Greece, Ireland, Italy, Portugal and Spain, and zero otherwise (*GIIPS*), and a country-level proxy funding liquidity risk, which is equal to the daily country-level volume of outstanding Certificates of Deposits *(CD Volume)* in Panel A and the daily country-level average of 5-year CDS spreads of local banks (*Local Banks' CDS*) in Panel B. All regressions include day fixed effects and country-month fixed effects. t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: Funding liquidity risk proxied by outstanding CD volume

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	-0.056***	-0.200	-0.045	-0.096***	0.022
	(-3.06)	(-0.87)	(-1.64)	(-3.09)	(1.65)
Unsecured Volume	0.0004	0.002**	0.0002	-0.0005	-0.0004*
	(0.92)	(2.00)	(0.30)	(-0.47)	(-1.77)
GIIPS*Unsecured Volume	-0.018***	-0.002	-0.003	-0.039***	-0.002
	(-4.44)	(-0.27)	(-0.76)	(-4.43)	(-0.19)
GIIPS*Sovereign CDS	0.073***	0.143	0.038	0.178***	-0.013
	(3.77)	(0.74)	(1.52)	(4.50)	(-0.71)
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
N	7362	815	3555	1658	837
r2	0.980	0.777	0.950	0.949	0.947

Panel B: Funding liquidity risk proxied by CDS spreads

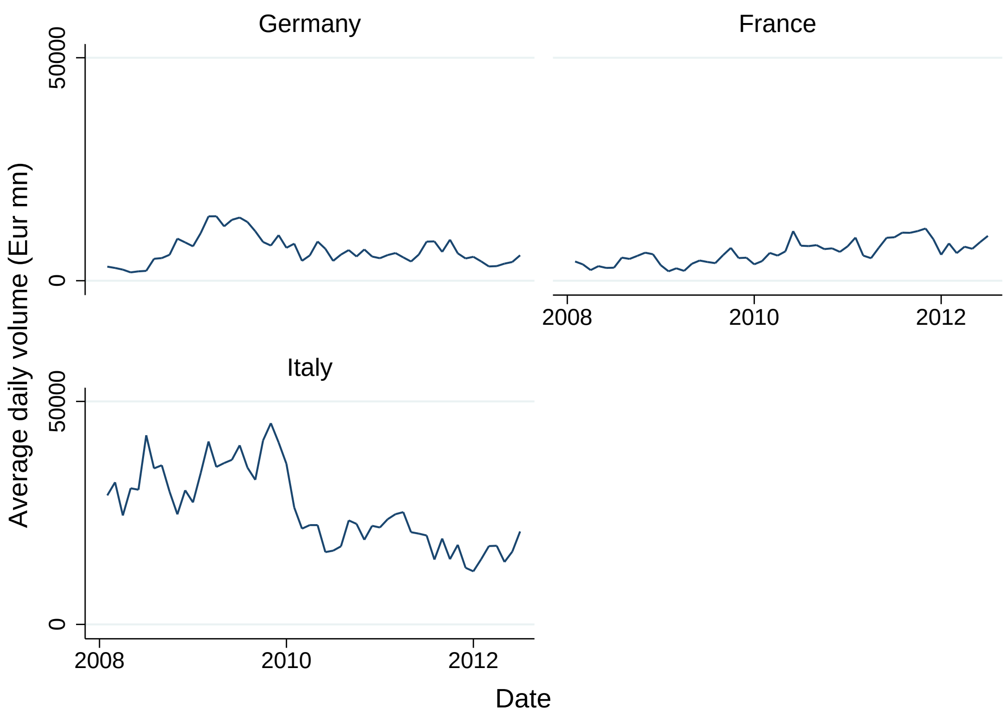
	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2011 S2	(6) 2012 S1
Sovereign CDS	-0.038**	-0.173	-0.019	-0.073**	0.019	
	(-2.30)	(-0.69)	(-0.74)	(-2.58)	(1.60)	
Local Banks CDS	-0.017	-0.077	-0.025*	-0.004	0.018	
	(-1.44)	(-1.09)	(-1.84)	(-0.21)	(1.46)	
GIIPS*Local Banks CDS	0.039**	0.027	0.035**	0.080**	0.011	
	(2.50)	(0.79)	(2.52)	(2.41)	(0.50)	
GIIPS*Sovereign CDS	0.040**	0.023	0.005	0.134***	-0.034	
	(2.08)	(0.12)	(0.21)	(3.37)	(-1.31)	
Day FE	Yes	Yes	Yes	Yes	Yes	
Country Month FE	Yes	Yes	Yes	Yes	Yes	
N	7683	815	3821	1713	837	
r2	0.980	0.771	0.952	0.949	0.947	

1.8 Appendix

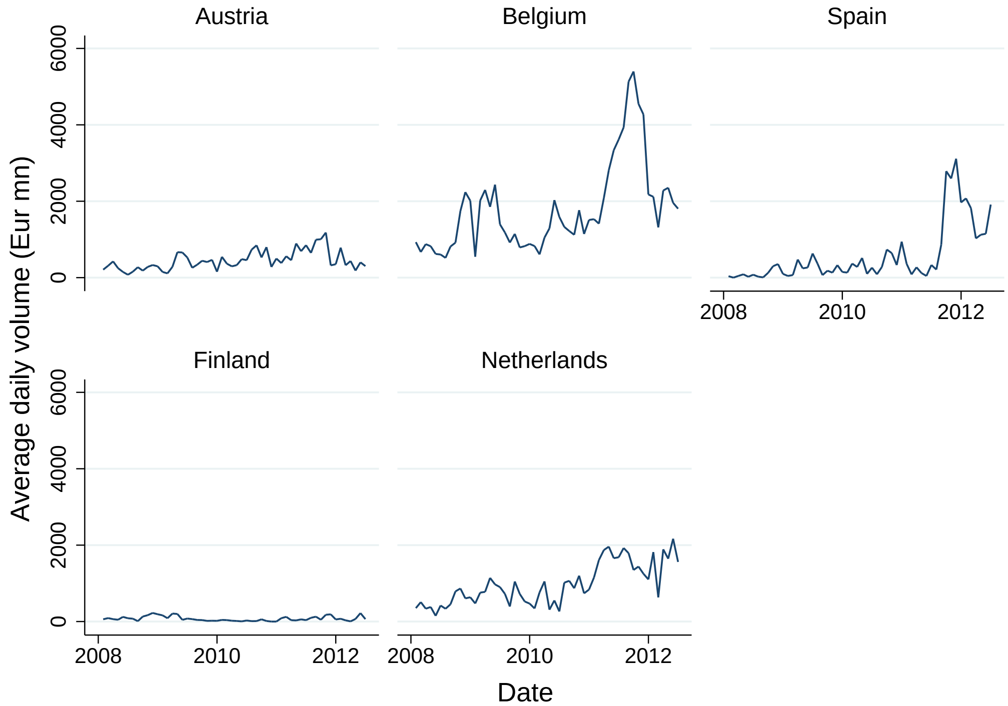
FIGURE 1.6: **Evolution of the volume of repo transactions in the Eurozone by country, 2008-2012 S1**

This figure presents the evolution of the average daily volume of General Collateral (GC) repo in the Eurozone over our sample period, between January 2008 and June 2012, by country. All amounts are in m, but each panel uses a different scale. Panel A is restricted to Germany, Italy and France. Panel B presents all other countries that did not seek foreign assistance through a bailout program. Panel C is restricted to countries that entered assistance programs (Ireland, Portugal and Greece). The start dates of bailout programs are indicated by vertical red lines.

Panel A: Germany, France, Italy



Panel B: Austria, Belgium, Spain, Finland, the Netherlands



Panel C: Greece, Ireland, Portugal

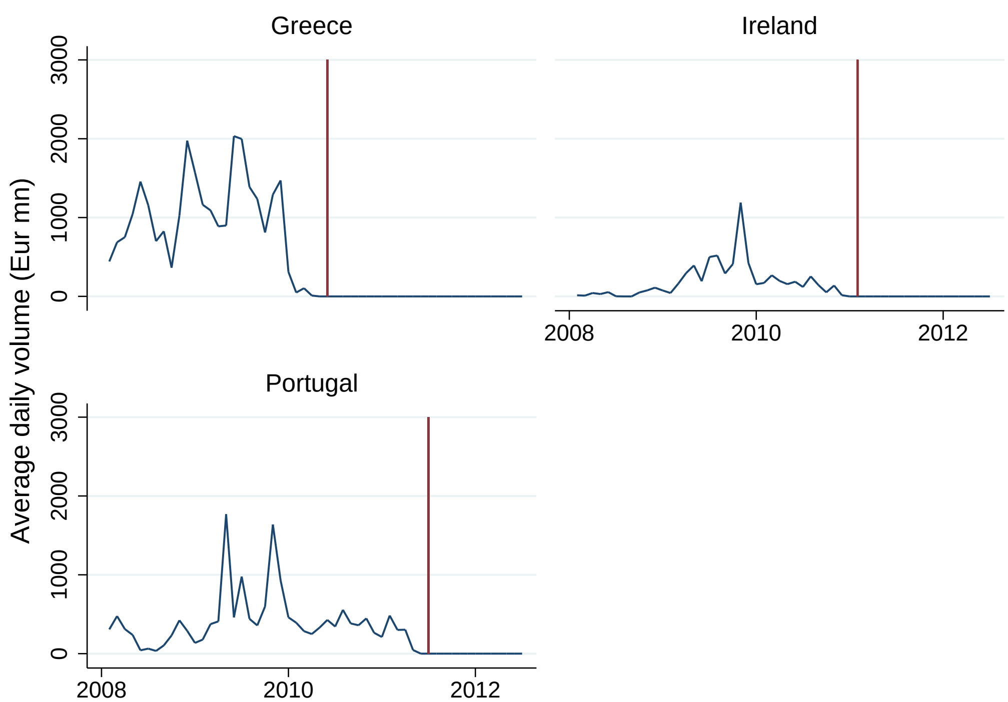


Figure 1.7: **Relationship between repo rates and sovereign CDS spreads**

This figure presents a scatter plot of the relationship between the average daily repo rate and the average daily sovereign CDS spread, across the 11 repo markets in our data. Each dot corresponds to one day. On the x-axis, we report the average sovereign CDS spread across the 11 countries. On the y-axis, we report the average difference between the repo rate and the ECB deposit rate across the same 11 countries. Our data has 1,149 observations, corresponding to all days between Jan 1, 2008 and June 30, 2012. The coefficient of the regression of repo rates on CDS spreads is -0.06, with an heteroskedacity-adjusted t-statistic of -14.01.

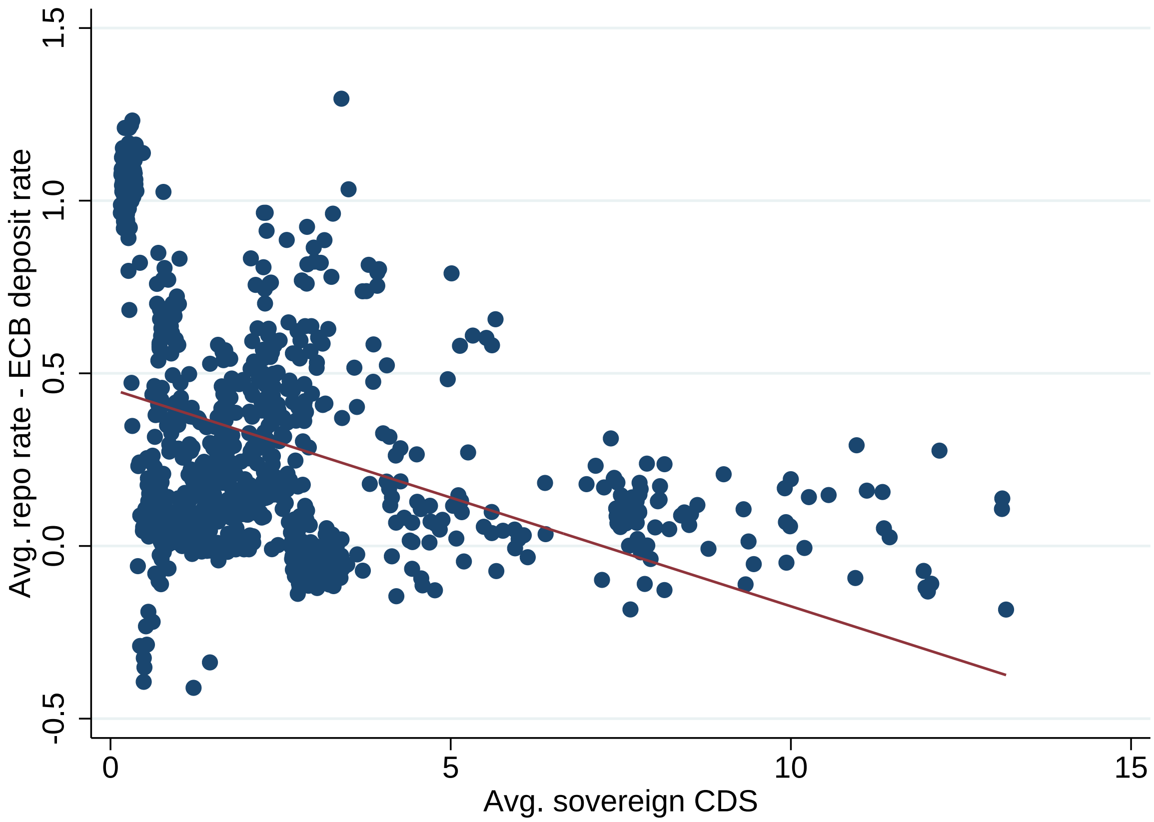
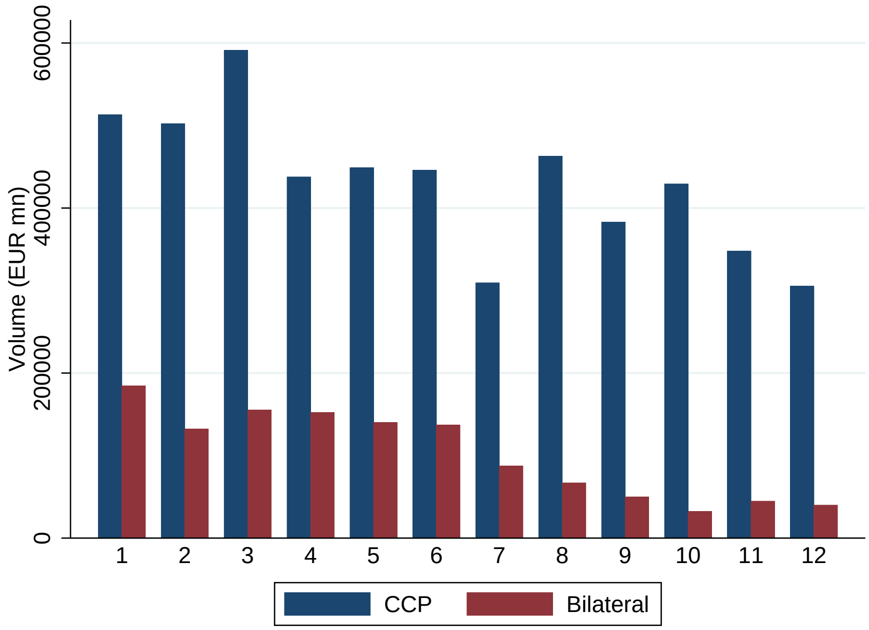


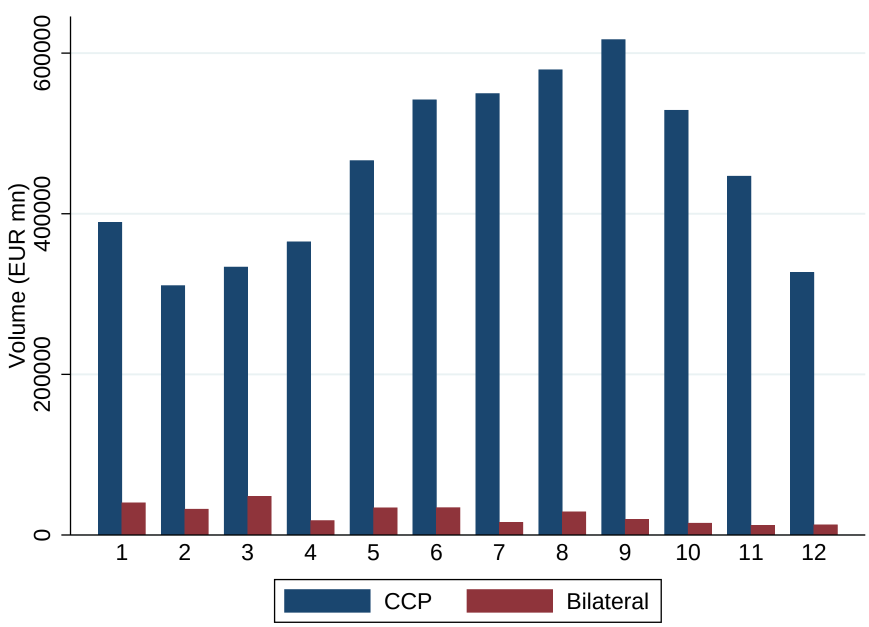
FIGURE 1.8: **Monthly volumes of CCP-cleared versus bilateral repo transactions in 2011**

This figure presents volumes of CCP-based and bilateral GC repo transactions in the Eurozone for each month of 2011. Panel A presents volume for GIIPS countries for which data are available (Italy, Portugal and Spain). Panel B presents volume for all Non-GIIPS countries in our dataset. All amounts are in m.

Panel A: Italy, Portugal, and Spain

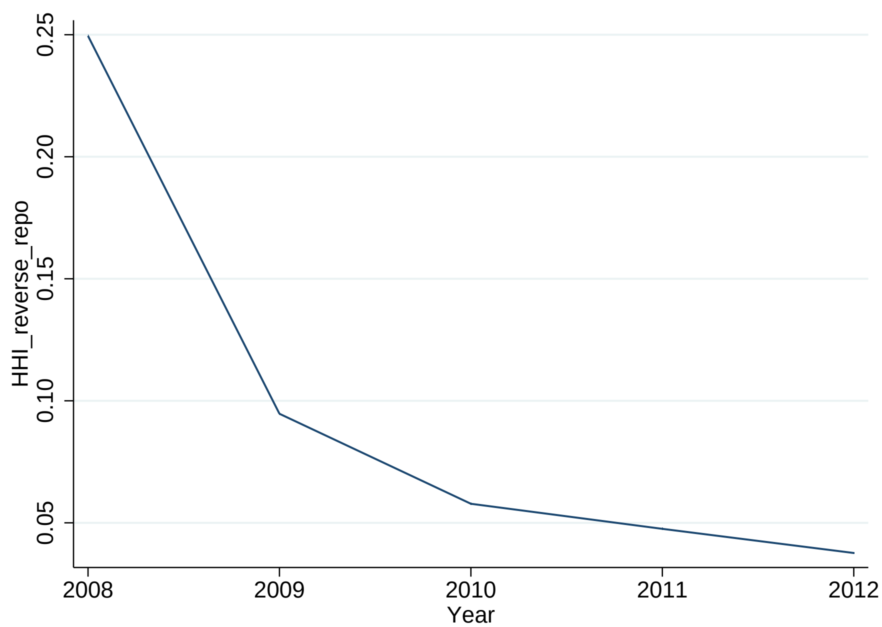


Panel B: Non-GIIPS Countries



]**Concentration on the CCP cleared Repo Market** Panel A presents the annual percentage share of reverse repos by the top 5, 10 and 20 largest European banks as reported in the ECB Money Market Surveys published annually from 2009 to 2014. Panel B presents, the evolution of the Herfindahl-Hirschman Index, which is calculated based on reverse repo data from Bankscope.

Panel A: Share of largest participants to CCP-cleared repo



Panel B: Herfindahl-Hirschman Index of reverse repo market concentration

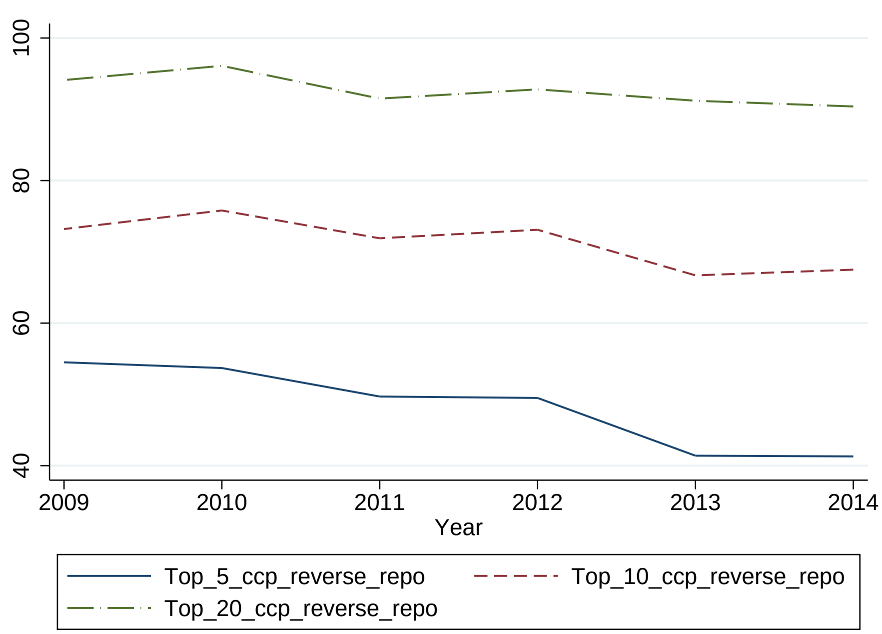


Table A1:GC repo rates and sovereign CDS spreads – Robustness checks

This table reports the estimates of fixed-effect panel regressions in which the dependent variable is the country-level average daily general collateral (GC) repurchase agreement rate minus the ECB deposit facility rate (*Repo Rate-ECB Deposit Rate*). In Panel A, the explanatory variable is the daily country-level one-year sovereign credit default swap rate (*Sovereign CDS*) and its interaction with an indicator variable that is equal to one for Greece, Ireland, Italy, Portugal and Spain, and zero otherwise (*GIIPS*). In Panel B, we run the same regression with the 5-year sovereign CDS rate (as in Table 3, Panel B) excluding Italy from the sample. All regressions include day and country-month fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the daily level. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively

Panel A: Repo-to-CDS spread sensitivity with one-year sovereign CDS

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	-0.032**	-0.350	-0.017	-0.064**	0.005
	(-2.10)	(-1.41)	(-0.72)	(-2.30)	(0.45)
GIIPS*Sovereign CDS	0.055***	0.122	0.022	0.180***	-0.012
	(3.20)	(0.52)	(1.02)	(5.40)	(-0.79)
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
Number of observations	7151	846	3653	1460	716
r2	0.979	0.793	0.947	0.944	0.945

Panel B: Funding liquidity risk proxied by CDS spreads

(6) 2012 S1	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2011 S2
Sovereign CDS	-0.037**	-0.108	-0.033	-0.089***	0.009
	(-2.52)	(-0.44)	(-1.26)	(-3.49)	(0.68)
GIIPS*Sovereign CDS	0.032*	0.007	0.034	0.129***	-0.009
	(1.93)	(0.03)	(1.39)	(3.03)	(-0.46)
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
Number of observations	7324	813	3918	1564	760
r2	0.983	0.766	0.948	0.960	0.950

Table A2:Controlling for ECB haircut policy

This table reports the estimates of equation (6). All regressions include day and country-month fixed effects. The average ECB haircut (*ECB HC*) is computed as the average prevailing haircut on all sovereigns of the country. t-statistics are presented in parentheses. Standard errors are clustered at the daily level. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: Sensitivity of repo rates to sovereign CDS spreads

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	0.033**	0.00123	0.076**	0.007	
	(2.31)	(0.13)	(2.28)	(0.56)	
ECB HC	-0.0003	-0.013	-0.009	0.002	
	(-0.05)	(-0.34)	(-0.39)	(0.51)	
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
Number of observations	4,173	1,462	1,809	875	
r2	0.957	0.923	0.949	0.946	

Panel B: Sensitivity of repo rates to sovereign CDS spreads – GIIPS vs. non-GIIPS

(6) 2012 S1	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2011 S2
Sovereign CDS	-0.090***	-0.138***	-0.108***	0.016	
	(-4.34)	(-4.10)	(-3.35)	(1.18)	
GIIPS*Sovereign CDS	0.128***	0.135***	0.208***	-0.010	
	(5.57)	(4.18)	(5.23)	(-0.52)	
ECB HC	-0.004	-0.005	-0.008	0.003	
	(-0.51)	(-0.14)	(-0.29)	(0.61)	
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
Number of observations	4,173	1,462	1,809	875	
r2	0.957	0.923	0.949	0.946	

Table A2: Controlling for country-level exposure to risk

This table reports the estimates of equation (7). All regressions include day fixed effects and country-month fixed effects. We also include the Vixx Interacted with country fixed effects. t-statistics are presented in parentheses. Standard errors are clustered at the daily level. *, **, and *** denote statistical significance at the 10%-, 5%-, and 1%-level, respectively.

Panel A: Sensitivity of repo rates to sovereign CDS spreads

	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2012 S1
Sovereign CDS	0.016	-0.149*	-0.001	0.073**	0.012
	(1.32)	(-1.69)	(-0.16)	(2.09)	(0.85)
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
Country FE*Vixx	Yes	Yes	Yes	Yes	Yes
Number of obs.	8,437	989	4,156	1,817	882
r2	0.981	0.786	0.951	0.949	0.946

Panel B: Sensitivity of repo rates to sovereign CDS spreads – GIIPS vs. non-GIIPS

(6) 2012 S1	(1) 2008-2012 S1	(2) 2008-Lehman	(3) 2009-2010	(4) 2011	(5) 2011 S2
Sovereign CDS	-0.060***	-0.089	-0.028	-0.121***	0.023
	(-3.30)	(-0.28)	(-1.01)	(-3.81)	(1.61)
GIIPSSovereign CDS	0.079***	-0.056	0.026	0.225***	-0.014
	(4.05)	(-0.21)	(0.96)	(5.60)	(-0.63)
Day FE	Yes	Yes	Yes	Yes	Yes
Country Month FE	Yes	Yes	Yes	Yes	Yes
Country FE*Vixx	Yes	Yes	Yes	Yes	Yes
Number of obs.	8,437	989	4,156	1,817	882
r2	0.981	0.786	0.951	0.951	0.946

Chapter 2

Can Big Players Affect Aggregate Lending?

2.1 Introduction

The past decades have seen the rise of a few big banking groups dominating the US banking sector. The share of total assets held by the top 5 banking groups increased from 13 % in 1976 to 48 % in 2010, as shown in figure I, following the deregulation wave of the 1980s-1990s (Berger, Demsetz and Strahan, 2009). A similar trend has also been witnessed in Europe and in Japan. This paper focuses on a particular channel through which such a high concentration level may impact, systematically, aggregate lending by the banking sector: the transmission of banking groups' idiosyncratic credit supply shocks. Recent papers have argued that this mechanism, along with the rise in banking sectors' concentration, has become a key determinant of aggregate lending. This paper uses a new methodology to address this issue and shows that banking groups's credit supply shocks role is likely to be much more limited.

To illustrate the motivation of this paper, I begin with a simple example. Imagine a country whose banking sector is made of a high number of small independent banks of equal sizes: a credit supply shock hitting one of them will bear no consequences at the macroeconomic level as this bank's share of aggregate lending is negligible. As a consequence, aggregate fluctuations of credit will depend upon aggregate shocks such as crises, wars or productivity shocks. Now assume that one banking group, e.g. Bank Of America, acquires all of the previously independent small banks, so that the banking sector becomes highly concentrated. If Bank Of America does not interfere in the daily business of their subsidiaries, the banking sector will be exactly similar to the previous situation: Bank Of America is just the sum of small banks behaving as if they were independent. On the other hand, if Bank of America affects similarly its subsidiaries lending, through the transmission of idiosyncratic group-level credit supply shocks, those shocks might have the potential to affect aggregate lending as they would be transmitted to entire country's banking sector. To be even more concrete, let's assume that on a given date the management of Bank of America decides that each of its subsidiary must decrease its lending by 2%, then aggregate lending will decrease by 2%. In turn, if Bank of America transmits systematically group level credit supply idiosyncratic shocks to its subsidiaries, aggregate lending fluctuations may differ widely compared to the case where all banks are small and independent.

A recent literature argues that this mechanism is a major driver of aggregate lending, explaining up to 40% of its fluctuations (Amiti and Weinstein, 2013). Such a result could have wide implications, both from a theoretical and regulatory perspectives. From a theoretical point of view this would imply a shift of macroeconomics theory away from model based on representative banks. For monetary policy analysis, this would mean that focusing on aggregate measures may be misleading: a close analysis and supervision of the biggest banking groups' lending policies could be much more efficient. Imagine for example that a decrease in lending is due to exogenous negative supply shocks of a few big groups, then decreasing the interest rate in the whole economy may not be appropriate. More generaly, such a systematic exposition of credit supply to a few big groups could justify a closer regulation of banking groups lending policies.

In this paper, I take a new approach to this issue that leads to a much lower estimate of the impact of banking groups' supply shocks on aggregate lending. This paper's innovation is that, contrary to the existing literature (Amiti and Weinstein 2013, Buch and Neugebauer 2011, Bremus, Buch, Russ and Schnitzer 2013), I do not treat a banking group as being one single entity, but a collection of local subsidiaries. The intuition is the following: for banking groups' credit supply shocks to impact aggregate lending, they must be transmitted trough their local subsidiaries. My conclusion is based upon the finding that subsidiaries of a given banking group behave largely as if they were independent from each other. In turn, banking groups being similar to a collection a small independent banks, they can not be expected to generate large fluctuations of aggregate lending.

To do so, I use banking groups' acquisitions of new subsidiaries. More precisely, I test wether or not lending comovement between a newly acquired subsidiary and existing subsidiaries of the acquiring banking group increases around the acquisition date, in a classic Diff-In-Diff setup. Intuitively, if banking groups transmit similar supply shocks to their subsidiaries, then the lending comovement of two subsidiaries of the same group should be higher than the one of two independent banks, as subsidiaries are affected by the same group level shocks[1]. More precisely, the higher the increase in comovement, the higher the strength of such shocks and in turn their potential impact on aggregate lending fluctuations.

This paper's first contribution is to show that banking groups do systematically influence their subsidiaries lending: the lending growth's correlation between the newly acquired subsidiary and existing ones increases, on average, by 70% after the acquisition date, everything else being equal. This is an interesting result in itself as it complements the existing literature on the transmission of shocks within bankin groups, that typically rely on event studies (Peek and Rosengreen 1997, 2000, Gilje, Loutskina and Strahan 2013), by showing that lending comovement exist within a banking group on a systematic basis. The effect is immediate (the bulk of the increase in comovement happens within 12 months after the acquisition) and permanent (I look up till 4 years after the acquisition). This result is robust to alternative explanations such as a shift in the borrower base (the borrowers of the newly acquired bank becomes more similar to the ones of the other subsidiaries), are not driven by factors common to all subsidiaries of banking groups (wholesale funding shocks for example) and can not be, at least entirely, explained by risk sharing accross subsidiaries.

I then show however that banking groups credit supply shocks' can not be expected to be a first order driver of subsidiaries' lending policies, and in turn of aggregate lending variations. This is because the absolute level of correlation after the acquisition stays relatively low, increasing from 6% to 10% on average. Analytically, I find that the variance of those shocks is simply too small, compared to the overall variance of subsidiaries' lending growth, so that they can not explain more than 5%, on average, of subsidiaries' lending growth variations. A large share of banking groups subsidiaries lending polices are unexplained by those shocks. Intuitively, they behave much more as if they were independent banks than similar entities whose lending policies were primarily affected by common group level credit supply shocks.

As a consequence, banking groups can not be expected to be primary dirvers of aggregate lending

[1] I acknowledge that a banking group may also affect each of its subsidiary in a different way. But the transmission of different shocks to different subsidiaries will have no impact at the aggregate level by the law of large number.

fluctuations. I estimate that they may explain up to 5% of aggregate lending variations in the 1990's-2000's a result much lower than found previously. This still represents a qualitative change compared to the 80's, when the lower degree of US banking sector's concentration resulted in banking groups supply shocks being negligible for aggregate lending. That being said, this paper is not about claiming that US biggest banking groups are not systemically important. Its findings are relatively orthogonal to the systemic risk literature (Acharya *et al.* 2010 , Adrian and Brunnermeier 2011) that focuses on the risk that such institutions generate in crisis times. It is interested instead in the potential effect of big banking groups in generating systematically meaningful aggregate lending fluctuations.

The natural way to think about such shocks are group level instructions about credit growth target transmitted to their subsidiaries or decisions about internal funding allocation between those subsidiaries. The more direct evidence comes from De Haas and Kirschenmann (2013) who interviewed around 200 heads of subsidiaries. More than 80% of the interviewees declared to be affected by their banking group trough either one of those two factors. Following Stein (2002), a related literature focuses on the incentives for banking groups to rely more on hard information compared to smaller local banks (Canales and Nanda (2012), Liberti and Mian (2009), Skrastins and Vig (2013), Berger *et al.* (2005)). As explained by Canales and Nanda (2012), this is linked to the lower degree of autonomy of local loan officers in banking groups compared to decentralized smaller banks. All in all, this gives a strong support to the claim that banking group level shocks indeed exist.

However, this paper's methology, contrary to event studies, has the drawback that the rise in comovement could be due to others factors different from group level idiosyncratic shocks, especially transmission of liquidity/capital shocks[2] or more globally risk sharing across banking groups' subsidiaries. If banking groups only impacted their subsidiaries by redistributing idiosyncratic shocks hitting them, then banking groups should not change the way aggregate lending fluctuate[3].

[2]There is a large literature on this subject beginning with Peek and Rosengreen (1997, 2000). Recent papers include Liberti and Sturgess (2013), Gilje, Loutskina and Strahan (2013), Cetorelli and Goldberg (2011, 2012) , Schnabl (2012).

[3]This is just to mean that when at the macro level, idiosyncratic shocks of individual subsidiaries already cancel out.

I however show that the observed rise in comovement is quantitatively equivalent for acquisitions of both relatively small and large new subsidiaries indicating that liquidity shocks' transmission can not be the only explanation, large subsidiaries being expected to be less constraint by the overall funding/capital position of the banking groups (Houston, James and Marcus,1997). But as I will not be able to fully discriminate between both explanations, this means that my estimates should be taken as an upward estimate of the strength of group level credit supply shocks, which only strengthens the claim that banking groups may not be responsible for a large share of aggregate lending fluctuations.

The rest of the paper is organized as follows: section 2 briefly discusses the related literature, section 3 details the statistical framework, the empirical strategy and the data on which is based this paper. Section 4 presents the results of this paper and discusses it. In section 5 are presented various robustness checks. Section 7 concludes.

2.2 Related Literature

This paper joins a recent literature that aims at understanding the systematic impact of banking groups credit supply shocks on aggregate lending. Buch and Neugebauer (2011) and Bremus, Buch, Russ and Schnitzer (2013) estimate that big bank idiosyncratic shocks may explain around 10% of per capita GDP growth variations for a panel of European countries. Amiti and Weinstein (2013) estimate that banks' idiosyncratic shocks explained around 40 % in Japan for the 1990-2010 period, a number much higher than what is found in this paper.

Amiti and Weinstein (2013), Buch and Neugebauer (2011) and Bremus, Buch, Russ and Schnitzer (2013) all rely on a similar type of methodology. They first estimate contemporaneous idiosyncratic shocks hitting each bank in their sample as being the difference between a bank aggregate loan growth in a given year and the average aggregate loan growth among all banks in the same country. They then build a "'Banking Granular"', which is the bank size weighted sum of their estimates of idiosyncratic shocks and regress either aggregate lending or per capita GDP growth on it. The intuition is the same as the one described in my model: the bigger a bank, the more important for aggregate fluctuations its specific shocks will be. Amiti and Weinstein (2013) have loan level data, so they are able to go as step further and net out the effects of shocks hitting the borrowers in the spirit of Khwaja and Mian (2008), but the intuition underlying their methodology is the same as the others papers. Compared to this paper, this method has the advantage that they may capture time variation in the amplitude of shocks, whereas my method only captures the average shock systematically hitting BHC's subsidiaries.

However, this has one drawback compared to the methodology used in this paper as their (contemporaneous) estimates of idiosyncratic shocks are likely to capture the fact that unobserved variables commonly drive the biggest banks lending behavior in the same direction as aggregate variables. I show in the last section that the main reason why their results differ from mine is that using a "'Granular"' method suffer from an omitted variable bias.

This paper also complements the effect of banking groups on their subsidiaries lending policies. Its novelty is to study it in a systematic way and to try to disentangle between pure risk sharing or transmission of shocks across subsidiaries and group level shocks that has been the main focus of the existing literature as discussed in the introduction.

It also sheds light on a new aspect of concentration risk that may be of interest for regulators. The existing literature, as summarized by Cetorelli et al. (2007), does not give clear predictions on the impact of the banking sector concentration on financial stability. On one hand, a higher concentrated, less competitive, banking sector may enhance financial stability through higher profit that provides buffer in times of crisis, better diversification of large banks and easier monitoring of a small number of institutions. On the other hand, concentration may reduce competition, lead to the apparition of "'Too big too fail"' banks and give unfair political power to a few financial institutions. This paper helps further understanding how big banking groups may affect aggregate credit by looking at their direct influence on their subsidiaries lending growth. It shows that indeed, large banking groups transmit shocks to their subsidiaries. Therefore, banking markets concentration exposes aggregate lending to idiosyncratic shocks hitting a small number of global banks which can be detrimental to financial stability and lead to an increase in aggregate lending volatility. If this paper shows that this risk is still limited today, it may become a concern if the historical trends in concentration continue.

Finally, this paper builds upon the literature on the real effects of banks credit supply shocks. Indeed, if banks loans are easily substitutable (a firm can switch banks or turn to others type of financing), there are no reasons that supply side shocks will affect the overall supply of credit and hence. However, a large literature beginning with Peek and Rosengreen (1997, 2000) documents that credit supply shocks do affect firms borrowing capacities and have real economic consequences. Credit supply side shocks impacts the borrowing capacity of firms, this being especially true for small firms which are more likely to be credit constrained, (Khwaja and Mian (2008); Puri, Rocholl and Steffen (2011) ; Paravisini (2008)) which has direct consequences for their level of investment (Gan (2007)), employment (Chodorow-Reich (2012)) and exports activities (Amiti and Weinstein (2011)) as well as for the overall local economic activity Greenstone and Mas, (2013). Theoretically, this comes from the difficulty to transfer information produced through firm-creditor relationships (Petersen and Rajan (1994)) that are needed to overcome informations asymmetries (Stiglitz and Weiss (1981)).

2.3 Framework and empirical strategy

2.3.1 How idiosyncratic shocks to large banking groups may affect aggregate lending?

I begin by building a simple framework to formally express the intuitions on why banking groups' idiosyncratic shocks may affect aggregate lending of the banking sector. I detail my empirical strategy based on this framework in the next section. A banking group is defined as a group owning at least two banks subsidiaries. This framework is a statistical one and not a structural one. Its simplicity comes at a cost but its conclusions are strongly intuitive and do help to understand the role of big groups in affecting aggregate lending.

Building on Landier, Sraer and Thesmar (2013), who follow Gabaix (2011), I assume that a bank lending growth is the sum of a bank-specific and an aggregate shock. $L_{i,t}$ is the lending of bank i at date t and $\frac{\Delta L_{i,t}}{L_{i,t-1}}$ is the lending growth of bank i at date t:

$$LG_{i,t} = \frac{\Delta L_{i,t}}{L_{i,t-1}} = a_t + \eta_{i,t} \tag{2.1}$$

Where a_t is a common shock affecting all US banks at date t and $\eta_{i,t}$ is the idiosyncratic shock of bank i. In practice I will also take into account local (state level) shocks affecting bank i lending, but for simplicity I assume here that local conditions do not affect lending[4].

Now if bank i is a subsidiary of a banking group, I further decompose its lending growth as being the sum of a banking group specific shock, a bank specific shock and an aggregate shock[5]. In this case, the lending growth of subsidiary i of banking group k at date t is :

$$LG_{SUB_{i,k,t}} = \frac{\Delta L_{i,k,t}}{L_{i,k,t-1}} = a_t + b_{k,t} + \eta_{i,k,t} \tag{2.2}$$

Where $b_{k,t}$ and $\eta_{i,t}$ are respectively the banking group and the subsidiary idiosyncratic shocks. One can think of $b_{k,t}$ as the global decisions over expansion at the banking group level or as the effect of a liquidity shock hitting the banking group that is transmitted to all of its subsidiaries trough internal capital markets. $\eta_{i,k,t}$ may be thought as being local staff decisions over lending growth for example. Now summing over all the subsidiaries i of the banking group k, lending growth $\frac{\Delta L_{k,t}}{L_{k,t-1}}$ of the banking group k at date t is:

[4] It is straightforward to include state level shocks in the framework.

[5] Here, I focus on a group level shock similarly affecting all subsidiaries of a group. I do not reject the possibility that banking groups also transmit different shocks to their subsidiaries. They are neglected here because as long as they are uncorrelated, they will cancel out in the aggregate because of the law of large numbers.

$$LG_{GROUP_{k,t}} = \frac{\Delta L_{k,t}}{L_{k,t-1}} = \frac{\sum_i \Delta L_{i,t}}{L_{k,t-1}} = \frac{\sum_i (a_t + b_{k,t} + \eta_{i,t}) * L_{i,t-1}}{L_{k,t-1}}$$
$$= a_t + b_{k,t} + \sum_i \frac{\eta_{i,k,t} * L_{i,t-1}}{L_{k,t-1}} \tag{2.3}$$

Now at the national level, aggregate lending growth will be the size weighted sum of all banks lending growth, and can therefore be decomposed between the sum of a common shocks, the weighted sum of banking group idiosyncratic shocks and the weighted sum of idiosyncratic shocks hitting subsidiaries of Bank Holding Companies (BHCs[6]) and independent banks:

$$LG_{AGGREGATE_t} = \frac{\Delta L_t}{L_{t-1}} = a_t + \sum_k b_{k,t} * \frac{L_{k,t-1}}{L_{t-1}} + \sum_{i,k} \eta_{i,k,t} * \frac{L_{i,k,t-1}}{L_{t-1}} + \sum_l \gamma_{l,t} * \frac{L_{l,t-1}}{L_{t-1}} \tag{2.4}$$

Where k indexes BHCs, i subsidiaries of BHCs and l independent banks. $b_{k,t}$ are banking group idiosyncratic shocks of volatility σ_{BHC}, $\eta_{i,k,t}$ are idiosyncratic shocks of banking group subsidiaries of volatility σ_{sub} and $\gamma_{l,t}$ are idiosyncratic shocks of independent banks of volatility σ_{ind}. I implicitly assume common shocks and idiosyncratic shocks of BHCs, subsidiaries and independent banks are i.i.d. National credit growth variance, assuming constant banks and banking group shares, is given by:

$$\underbrace{Var(LG_{AGGREGATE_t})}_{\text{Aggregate lending Variance}} = \sigma^2_{agg} + \sigma^2_{BHC} * \underbrace{\sum_k LG^2_{GROUP_{k,t}}}_{Hbhc} + \sigma^2_{sub} * \underbrace{\sum_{i,k} LG^2_{SUB_{i,k,t}}}_{Hsub} + \sigma^2_{ind} * \underbrace{\sum_l {LG_{i,t}}^2}_{Hind} \tag{2.5}$$

Where $Hbhc$, $Hsub$ and $Hind$ are respectively the Herfindahl indexes of BHCs, BHCs subsidiaries and independent banks. Equation 5 contains the main intuition of the model: the share of aggregate lending fluctuations explained by idiosyncratic shocks hitting BHCs can be proxied by:

[6] I will use Bank Holding Company (BHC) or banking group interchangeably in the rest of this paper.

$$\frac{\sigma_{BHC}^2 * Hbhc}{\text{Aggregate Lending Variance}} \tag{2.6}$$

This equation contains the main intuitions of this framework. It states first that for banking groups idiosyncratic shocks to matter at the aggregate level the banking sector should be sufficiently concentrated ($Hbhc$). However, it also shows that big banking groups dominating the US banking market is not a sufficient condition. It also requires the variance of their credit supply shocks to be high enough (σ_{BHC}). Intuitively, this means that banking groups can affect aggregate lending only as long as they sufficiently affect similarly their own subsidiaries lending. Indeed, as discussed in the introduction, if local subsidiaries behave as if they were independent from each other, then banking groups can not be expected to account for large aggregate credit fluctuations.

$Hbhc$ is directly computable from the data. It is represented in Figure 2. It raised significantly over the last 4 decades following the rise of the concentration in the banking sector. The challenge is to get an estimate of σ_{BHC}.

2.3.2 Empirical strategy: recovering an estimate of σ_{BHC} using acquisitions by banking groups

This paper's empirical strategy to recover an estimate of σ_{BHC} uses new acquisitions by existing banking groups. The intuition is that banking groups shocks should make lending fluctuations between subsidiaries more similar than if they were independent, so that the lending growth co-movement between the newly acquired subsidiary and the existing ones should increase after the acquisition date. More precisely, σ_{BHC} is estimated by the change in lending growth covariance between a newly acquired bank and the subsidiaries that were already owned by the acquiring banking group around the date of acquisition.

The analytical proof is the following. Let's consider the acquisition of bank j by a banking group k. Building upon the statistical framework of the previous section, its lending growth $LG_{ACQ_{j,k,t}}$ is equal to:

$$LG_{ACQ_{j,k,t}} = \begin{cases} agg_t + \eta_{j,k,t} & \text{Before the acquisition} \\ agg_t + b_{k,t} + \eta_{j,k,t} & \text{After the acquisition} \end{cases} \quad (2.7)$$

Where agg_t is an aggregate shock, $b_{k,t}$ a BHC k specific shock and $\eta_{j,k,t}$ is a bank level idiosyncratic shock. The key here is that j only becomes affected by BHC k shocks after it has been acquired by it. Turning to the subsidiaries of group k that were already owned by k before the acquisition of bank j. $LG_{SUB_{i,k,t}}$, the lending growth of each existing subsidiary i of k is equal to :

$$LG_{SUB_{i,k,t}} = \frac{\Delta L_{i,k,t}}{L_{i,k,t-1}} = agg_t + b_{k,t} + \eta_{i,k,t} \quad (2.8)$$

So, the average lending growth of all existing subsidiaries of BHC k, $LG_{AVGSUB_{k,t}}$, is equal to :

$$LG_{AVGSUB_{k,t}} = \frac{1}{N} * \sum_i \frac{\Delta L_{i,k,t}}{L_{i,k,t-1}} = agg_t + b_{k,t} + \frac{1}{N} * \sum_i \eta_{i,k,t} \quad (2.9)$$

where N is the number of subsidiaries of the BHC k. I now compute the lending growth covariance of j with the average lending growth of BHC k existing subsidiaries $LG_{AVGSUB_{k,t}}$ before and after the acquisition date. This is equal to:

$$Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}}) = \begin{cases} \sigma^2_{agg} & \text{Before the acquisition} \\ \sigma^2_{agg} + \sigma^2_{BHC} & \text{After the acquisition} \end{cases} \quad (2.10)$$

When j becomes a subsidiary of k, it becomes submitted to banking group k idiosyncratic shocks, increasing the lending growth comovement j and others subsidiaries of k. More precisely, as shown above, the increase in lending growth covariance between the two groups of banks is equal to the variance of banking group k idiosyncratic shocks. This gives one prediction as well as a method to compute an estimate of the variance of BHCs' idiosyncratic shocks:

- First, the lending growth covariance between a newly acquired bank and the others existing subsidiaries of the acquired BHC should increase.
- Secondly, the change in covariance can be used as an estimate of the variance of BHCs' idiosyncratic shocks.

Empirically, I test this hypothesis and recover and estimate of σ^2_{BHC} by running a Diff-In-Diff analysis of change in covariance between new and existing subsidiaries around acquisition dates. My baseline regression is the following:

$$Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}}) = \alpha_j + \gamma_t + \beta * POST_{j,t} + \eta_{jt} \tag{2.11}$$

Where j indexes a bank that is acquired by a BHC k on a given date, $LG_{ACQ_{j,k,t}}$ is the quarterly total loans growth of j , $LG_{AVGSUB_{k,t}}$ is the quarterly average of total loans growth of BHC k subsidiaries that were already subsidiaries of k the quarter preceding the acquisition of j. $Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}})$ is the lending growth covariance between those two groups of banks. It is computed on a 2 years moving window[7] (1 year before and 1 year after[8]). $POST_{j,t}$ is the 2 years moving average of a dummy equal to 1 after the acquisition date and 0 otherwise. I include an acquisition fixed effect α_j to control for invariant differences between acquisitions, a date fixed effect to control for aggregate shocks γ_t and allow standard errors at the acquisition level[9].

The coefficient of interest is β: it directly measures the increase in lending growth covariance following the acquisition and is my estimate of BHC's idiosyncratic shocks variance. I then use this estimate and uses equation (6) to recover an estimate of the share of aggregate lending variance that may be explained by banking groups's credit supply shocks.

I do not have an instrument for acquisitions, which means that any changes in the covariance may be endogenous: a group may choose to acquire a subsidiary because it anticipates that it is going to expand on similar markets than the subsidiaries it already owns, or because its overall

[7] All the results hold if I use a 4 years moving window. I have not tested others one.
[8] This means that the covariance is computed based on 9 observations, e.g. 9 quarters
[9] All results hold if I cluster at the acquisition*post level

growth prospects are similar to these of its subsidiaries, generating an increase in the lending growth covariance after the acquisition which will not be due to the change of ownership. I produce evidence however showing that this endogeneity problem is unlikely to be a real issue here. In particular, the covariance is flat before the acquisition and increases sharply just on the year of acquisition (see Figure 4). In robustness checks, I also address issues aimed at disentangling between risk sharing between subsidiaries or specific factors affecting all the subsidiaries of all banking groups.

2.4 Data

The main dataset I use is a quarterly panel of lending growth covariance between a newly acquired bank and other subsidiaries of the acquiring BHC upon the 1977-1994 period. The group of others subsidiaries of the acquiring BHC is limited to the subsidiaries that were already owned by the BHC at the date of acquisition. This will allow me to run Diff-in-Diff analysis of the lending growth covariance between those two groups of banks around the acquisition date in order to test whether or not common ownership drives up the lending growth covariance of banks.

My main analysis are ran on the 1977-1994 period because in 1995 the Riegle-Neal Act allowed BHCs to consolidate their balance sheets nation wide. In turn, this implies that after 1995 data on local subsidiaries lending is noisier. I however verify in a robustness check that all results hold when extending the period of analysis to the 1976 to 2010 period.

Bank Level Data The bank lending and ownership data comes from regulatory fillings, the FED Call Reports, from 1976 to 2010 which provide quarterly information on each US commercial bank. For each bank, I collect quarterly data on domestic total loans (rcon1400) [10], CI loans (rcon1600), deposits (rcon2200), total assets (rcon2170)[11], state of location (rssd9210) and its BHC (rssd9348). The total loans variable in the Call Reports is the sum of real estate, agricultural and Commercial and Industrial (CI) loans plus loans to individuals, to foreign governments and official institutions,

[10]Total loans is defined as the sum of rcon1400 and rcon2165 before 1983 as advised by Haan, Sumner and Yamashiro (2002) .

[11]I use only RCON serie for all lending variables as this serie focuses on domestic lending which is the geographical area of interest for this paper.

to depository institutions, acceptances of others banks and others loans. Real estate, agricultural, CI and loans to individuals represent together 96% of total loans on average. The second largest category is loans to depository institutions, which exclude federal funds transactions and cash and balances between depository institutions that maintain deposits accounts with each other.

If a bank does not have a BHC, I do as if it was its own BHC. Those banks will be the one identified as independent banks. I remove observations for which total assets is unavailable or negative and transform it into 2005 constant dollars. Then for each quarter, I compute total loans and CI loans growth rate at the bank level and replace each growth rate as a missing value if is higher than 50 percent, below -50 percent or if the bank merged with another bank in this quarter to ensure consistency of the data.

Main analysis are ran on the 1977-1994 period, before the Riegle Neal Act of 1995 that allowed BHCs to consolidate their balance sheets nation wide. This implies that after 1995, the identification of local subsidiaries is much more difficult as banking group tended to consolidate all their subsidiaries together. Before 1995, the assumption is made that a bank lends only in the state in which it is located as in Landier, Sraer and Thesmar (2013).

Identifying Bank Acquisitions, Acquiring BHC's Existing Subsidiaries and computing their lending growth covariance To identify acquisitions by BHCs I use the following procedure:

- I identify the quarter of acquisition of a bank by a BHC as the quarter when the BHC of this bank changes. Then, for each acquisition, I identify all subsidiaries owned by the acquiring BHC on the quarter preceding the acquisition. I do this on the 1976-2000 period.
- Then for each acquisition, I compute the quarterly mean of total loans growth of the group of already owned subsidiaries on a 12 years window around the acquisition date (6 years before/6 years after). A subsidiary in this group is included as long as its BHC does not change. I focus on a 12 years windows as to ensure consistency of the group of the subsidiaries of the acquiring group, as some of them may disappear through time (or the BHC itself).

- I then import the quarterly total loans growth of the newly acquired bank at each date of this 12 years window around its acquisition date and compute the quarterly covariance of total loans of the newly acquired bank with the quarterly mean of Total Loans growth of the group of previously owned subsidiaries. I do this on a 2 years moving average (1 year before/1 year after).
- A last word: all the growth rates are in absolute values, not in percentage. This explains the very small covariances values throughout this paper.

My final dataset is therefore a panel where, for each acquisition, I have the quarterly covariance of Total Loans growth between the newly acquired bank and the means of Total Loans growth for the group of subsidiaries that were owned by the acquiring BHC before the acquisition on a ten years window [12] around the acquisition date. I then restrict my panel to the 1977-1994[13] period for the reasons explained previously.

I also identify the state location of the BHC acquiring the bank as being the state in which this BHC has its larger share of assets at the first date when I find it in the date. If its larger share is lower than 40%, the state location of the BHC is missing.

My final dataset contains 5487 mergers. Descriptive statistics on the final sample of acquired banks and acquiring BHCs are given in table I. As it can be noted, the type of acquisitions is highly diverse. The smallest acquired bank has 0.8 millions dollars [14] and the largest more than 16 billions. Regarding the acquisition BHCs, around 20% of the acquisitions are made by top BHCs, defined as the top 50 BHCs in terms of assets the quarter preceding the acquisition. As expected, the average BHC is however much bigger than the average bank acquired (3.5 billions versus 62 millions in terms of on balance sheet total loans). Interestingly, an acquiring BHC in my sample acquired on average 24 banks. Finally, around 30% of acquisitions are acquisitions of banks that were already subsidiaries of a BHC. Figure III plots the number of in sample mergers per year.

[12] I loose the first and last year of the 12 years window due to the computation of the covariance on a 2 years moving average

[13] Here again, my sample begins only in 1977 and ends in 1994 (instead of 1976 and 1995) due to the moving average computation of covariances.

[14] All numbers are in 2005 dollars

2.5 Results

2.5.1 Do Banking Groups Systematically Transmit Shocks to Their Subsidiaries?

Graphical Analysis Before turning to the regression analysis, I begin by reporting a graphical analysis of my results. Figure IV plots the year to acquisition average covariance of total loans growth between the newly acquired bank and the average total loans growth rate of already owned subsidiaries at the time of acquisition from -5 years before the acquisition to 6 years after, "'controlling"' for aggregate shocks. To do so, I first subtract to each covariance on a given date the average covariance for banks that have not yet been acquired at this date (the equivalent of my control group in the baseline regression). I then average across all my acquisitions the value of the covariance on a year to acquisition basis from -5 to +6 years after the acquisition date.

The figure shows a clear break on the acquisition year (year 0 on the graph) suggesting that the covariance does rise sharply and immediately after the acquisition. One remark here: all covariances being measured on a 2 year centered window, the covariances computed on the acquisition year (year 0 on the graph) are computed partly using pre-acquisition covariances measures, which explains the gradual increase in covariance from the year of acquisition to the first year after acquisition (year 1 on the graph) [15]. This suggests that indeed, the lending growth covariance increases sharply after the acquisition date. To give an idea of the economic importance of the increase, the average lending growth covariance between a newly acquired bank and the already owned subsidiaries of the acquiring BHC is equal to 0.0003 in my sample. This implies that after the acquisition, the covariance rises from about 75%, from 0.003 to 0.005, which seems economically meaningful.

Baseline Specification As presented in the previous part, my baseline regression is:

$$Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}}) = \alpha_j + \gamma_t + \beta * POST_{j,t} + \eta_{j,k,t} \tag{2.12}$$

[15] For example: on the acquisition quarter, out of the nine data points used to measure the covariance, 4 are pre-acquisition values: the 4 preceding quarters. On the first quarter after the acquisition date, only 3 data points used to compute the covariance are pre-acquisition, etc...

Where j indexes a bank that is acquired by a BHC k on a given date, $LG_{ACQ_{j,k,t}}$ is the quarterly total loans growth of j , $LG_{AVGSUB_{k,t}}$ is the quarterly average of total loans growth of BHC k subsidiaries that were already subsidiaries of k the quarter preceding the acquisition of j. $Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}})$ is the lending growth covariance between those two groups of banks. It is computed on a 2 years moving window[16] (1 year before and 1 year after[17]). $POST_{j,t}$ is the 2 years centered moving average of a dummy equal to 1 after the acquisition date and 0 otherwise. I include an acquisition fixed effect α_j to control for invariant differences between acquisitions, a date fixed effect to control for aggregate shocks γ_t and allow standard errors at the acquisition level[18]. The coefficient of interest is β: it directly measures the increase in lending growth covariance following the acquisition and is my estimate of BHC's idiosyncratic shocks variance.

Table II presents the results. The covariance increases sharply after the acquisition. The results of the main specification are reported in column 1: $POST$ is equal to 0.00023 and is significant at the 1% level. In column 2, results are unchanged when I add time varying controls, namely the ratio of equity and deposits on assets as well as the log of total loans of the acquired bank. In column 3, I break down the POST dummy into year to acquisitions dummies around the acquisition date. All coefficients are measured relatively to the period -5 to -3 years before the acquisition date. It confirms the graphical analysis of figure IV presented previously: the covariance is flat before the acquisition, and rises as soon as the bank is acquired. Figure V plots the interactions coefficients of the column 3 specification: the effect is even clearer on the graph. In addition the effect is immediate and persistent confirming the existence of systematic banking groups supply shocks.

The effect is economically significant: the average rise in covariance is equal to 0.0023, in columns 1 and 2, which is equal to 70% of the average covariance for banks (see Panel C of Table I) that have not yet been acquired. In others words, the covariance rises up by 70% after the acquisition date, a finding similar to what was suggested by the graphical analysis in Figure IV. I checked in unreported tests that all results are hold when using correlation instead of covariance: correlation increases from 6% to 10%.

[16] All the results hold if I use a 4 years moving window. I have not tested others one.

[17] This means that the covariance is computed based on 9 observations, e.g. 9 quarters

[18] All results hold if I cluster at the acquisition*post level

In section 6, I run a bunch of robustness checks. I show in particular that this can not be explained by pure risk-sharing across subsidiaries, is not due to common factors affecting all the subsidiaries of all banking groups, is valid for acquisitions by top and smaller banking groups, is also found when looking at commercial and industrial loans and that it can not be explained by a local borrower base hypothesis [19]. I also split the sample period into three sub periods and extend my acquisitions' sample period to 2005. I finally show results based upon random matching. All results are left unchanged.

2.5.2 Do Global Bank Idiosyncratic Shocks Matter?

Now that I have an estimate of the variance of banking groups idiosyncratic shocks, I compute the contribution of banking groups' credit supply shocks to aggregate lending fluctuations using equation (6):

$$\frac{\sigma^2_{BHC} * Hbhc}{\sigma^2_{\text{US National Lending Growth Rate}}} \tag{2.13}$$

I rely upon the previous estimates of banking groups' shocks variance (table II columns 1 and 2). I finally compute the variance of aggregate lending growth for three periods: 1976-1995, 1995-2007 and 2000-2007 as it varies over time, especially following the great moderation. For each of those periods, I also compute the average value of the banking market herfindhal index.

I then compute the ratio of interest for each of those three periods. This gives me, assuming that the variance of BHCs' supply shocks is relatively constant over time[20], an estimate of the contribution of BHCs' supply shocks to aggregate lending fluctuations.[21] Results are reported in table III.

The first conclusion is that the contribution of banking groups' idiosyncratic shocks is relatively limited for all the three time periods. Interestingly, the contribution is higher between 1995-2007 than between 2000-2010 even if the HHI of the latter is higher. This effect is due to change in the

[19]Subsidiaries become to lend to the same borrowers after the acquisition.
[20]I verify it in section 6
[21]I assume here that throughout each period the HHI is constant and equal to its mean.

the volatility of aggregate lending: the 2000-2010 period witnessed two financial crisis, mechanically increasing the variance of national lending and decreasing the potential impact of banking groups's supply shocks. This is something that may seem at odds with the intuition that in time of crisis, big banking groups' supply may play a bigger role than in normal times. However, what is key here is to understand this is especially in times of stress that aggregate shocks become important which diminishes the relative importance of banking groups' supply shocks.

Figure VI illustrates well this effect. I plot there the variances of US national lending growth and aggregate shocks in the 1976-2010 periods. US national lending variance is the variance of the quarterly US national lending growth rate computed on a 5 years centered window and aggregate shocks are defined as being the average total loans growth rate across all US banks in my sample on a given quarter. Their variance is computed as well on a 5 years centered window.

The first remark is that aggregate lending variance follows closely the variance of aggregate shocks. Those are the primarily drivers of aggregate lending fluctuations not idiosyncratic shocks to a few big players. One can also clearly see on this figure the decrease in aggregate lending volatility following the Great Moderation and the two picks of aggregate shocks variance around the 2001 market crash and the 2007 financial crisis. It also shows that this is the decrease in aggregate shocks variance in the pre 2000 periods, leading to decrease in US aggregate lending growth variance, coupled with the rise in concentration in the banking sector (see figure II), that gave idiosyncratic shocks to big banks a relatively bigger role in explaining aggregate lending fluctuations in the 2000-2007 period compared to the 1976-1995 one. Then, the 2001 and 2007 crisis, and the associated rises in aggregate shocks variance, led to a relative decline of the importance of idiosyncratic shocks.

To sum up, if short term variations in aggregate shocks variance in the 2000's lead to more or less relevance for idiosyncratic shocks in impacting aggregate lending fluctuations, such shocks gained importance in the last three decades following the great moderation and the rise in the consolidation of the US banking sector but can not account for more than 5% of aggregate lending fluctuations in recent years.

2.5.3 Interpreting The Results: Banking Groups As A Collection Of Independent Banks

The previous sections showed that banking groups may be secondary drivers of aggregate lending fluctuations compared to aggregate shocks to explain aggregate lending growth fluctuations. This seems to suggest that even if common ownership increases the lending growth covariance (and correlation) of two subsidiaries by 70% compared to two independent banks, this is only of secondary importance in explaining subsidiary level lending fluctuations compared to subsidiaries own idiosyncratic shocks. Therefore, subsidiaries still seem to behave as they are mainly independent from each other. Another way of understanding this result, from an econometric point of view, is that BHCs' idiosyncratic shocks are relatively poor predictors of their subsidiaries' lending growth. The first thing to remember is that the overall lending growth correlation of an acquired bank with others subsidiaries of the acquiring group only increases from 6% to 10% after the acquisition date. This implies that there is a large lending supply's heterogeneity across subsidiaries of a given group. This is why one can not expect banking groups' supply shocks to have large effects on aggregate lending.

To test this idea more formally, I report in table IV subsidiaries-level lending growth regressions where I begin by including only a subsidiary fixed effect and then control for aggregate shocks, local (state level) shocks and BHC idiosyncratic shocks. I then compare the R squared of each regression and discuss the explanatory power of each type of variable. This analysis has a lot of potential windfalls from an econometric point of view but is interesting for broader discussion purposes. I proxy for aggregate shocks using the average total loans growth rate on a given quarter across all banks in my sample. I do similarly for state level shocks by taking the average across all banks located in a given state. For this latter proxy, I exclude from the average the value of a given subsidiary's growth rate (not doing so will lead to overestimation of the explanatory power of local shocks for states where there are only a few observations on a given date). I finally proxy for BHCs' idiosyncratic shocks by computing for each observation the average growth rate on a given date of all others subsidiaries of its BHC. I restrict the sample to the period 1976-1995 for the reasons explained previously (the Riegle-Niel Act of 1994) and to subsidiaries of BHCs (I exclude independent banks).

Looking at table IV, one can see that the R squared increases by 14% when controlling for aggregate and local shocks but only 3% when controlling for BHCs supply shocks: banking groups ownership is of secondary importance to understand the lending behavior of its subsidiaries. Idiosyncratic shocks are much more prevalent. In column 5, I also include as a control the average growth rate of others local subsidiaries belonging to the same BHC (the "'Local BHC Idio. Shocks"' variable) to take into account potential BHC level shocks at the local level such as a BHC's staff decision to expand locally. The R squared increases again by 3% but at this point it begins difficult to disentangle between different explanations (especially the fact that this increase may just be due to higher similarities between same BHC's subsidiaries's borrowers and others BHC's subsidiaries's borrowers). All in all, this helps to illustrate the claim of this paper that banking groups level shocks exist but are likely to play only marginal role in local subsidiaries lending decisions. In turn, banking groups may be considered as a collection of small local subsidiaries largely independent from each other.

2.6 Explaining the Differences With Previous Findings

My estimates of the role of big banks idiosyncratic shocks are much lower than what has been previously found (Buch and Neugebauer (2011) and Bremus, Buch, Russ and Schnitzer (2013)) in studies using empirical methods based on Gabaix (2011). I will show here that this is likely to be due to the fact that methods based on Gabaix (2011) are not adequate for the study of the banking sectors, as they do not take into account the fact that big and smaller banks may be exposed different aggregate shocks. I will finally show that if one controls for such differences, the use of the Gabaix (2011) method reaches conclusions that are close to the ones of this paper.

Econometrically speaking, I argue that Buch and Neugebauer (2011) and Bremus, Buch, Russ and Schnitzer (2013) regressions analysis suffer from an omitted variable bias. Indeed, they follow Gabaix (2011) to identify a given bank' idiosyncratic shocks by taking the difference between the average growth rate of all banks in their sample at a given date (the aggregate shock proxy) and this bank own growth rate, controlling for several factors including the size of the bank. Then, they regress aggregate total loans growth on the banks' size weighted average of those idiosyncratic shocks at each date (the Gabaix's Granular) and identify the contribution of idiosyncratic shocks as the share of R squared explained by the inclusion of the Gabaix's Granular in this regression. However, if big banks are affected by specific shocks, or more generally if they have a different "'beta"' to the average lending growth rate of US banks than smaller banks, then the identification of idiosyncratic shocks of big banks using Gabaix (2011) method may lead to an omitted variable bias. In this case, one should actually compare the growth rates of the biggest banks with the average growth rate of all big banks and not only the average growth rates of all banks in the sample.

To test this I compare the explanatory power of small and big banks average lending growth rates to explain big banks lending growth fluctuations. The idea is that if the biggest banks behave differently that the others banks, the average lending growth rate of small banks would be a poor proxy for aggregate shocks hitting the biggest banks. In others words, the average lending growth rate of the biggest banks may be quite different from the average lending growth rate of smaller banks.

I first compute at each date the quarterly average growth rate of the top 50 banking groups[22] and the others banks [23]. The latter measure, the "'small banks aggregate shock"', will therefore be similar to the proxy for aggregate shocks used by previous studies when computing the Gabaix's Granular, as I have on average 9500 banks in my sample on a given quarter . The first one, the "'big banks aggregate shock"', will control for the biggest banks specificities. The rest of the analysis is made upon the 1994-2010 period, the "'Glass Riegle Act problem"' being of secondary importance for this discussion as I am working now at the BHC level.

I then turn to the relative power of both measures to explain the biggest banks lending fluctuations.

[22]In the entire section, bank lending is aggregated at the BHC level.
[23]All the following results are robust to taking the 50, 100 or 200 biggest BHCs

I begin by aggregating the top 50 banking groups total assets on each quarter[24], and then compute the growth rate of this measure (the aggregate total loans growth rate of the top 50s banks). I finally regress this measure on the "small banks aggregate shock". Results are reported in Panel 1 of table V. Column 1 shows that the R-squared is about 22%. In column 2 of panel 1, I add as a control "big banks aggregate shock", the average growth rate of the top 50 banking groups. As can be seen, the R-squared rises to 73%. This means that the biggest banks behave much differently than smaller banks in my sample and this is not taking into account by the average growth rate of all banks in the sample. As a consequence, identifying big banks idiosyncratic shocks following Gabaix (2011) method is likely to lead to an overestimation of their role.

I did an unreported parallel analysis for the aggregate total loans growth rate of small banks (all banks except the top 50s one) and the results are symmetric. I find that the "small bank aggregate shock" explain 76% of aggregate total loans growth rate of small banks and controlling for the "big banks aggregate shock" increase the R-squared by only 2%. This is coherent with the fact that the biggest BHCs are very specific, and that taking this fact into account is needed when trying to understand the factors influencing aggregate lending fluctuations.

Now, this omitted variable will lead to overestimate the role of big banks idiosyncratic shocks if the "big banks aggregate shock" is correlated with both the aggregate loans growth rate, which has to be the case given the large lending share of the biggest banks (see figure I), and the "Gabaix Granular", which will also be the case by the very definition of the "Gabaix Granular". To quantify the potential bias, I begin by regressing the US total loans growth rates first including only the "small banks aggregate shock" (excluding the top 50s banks), then adding the "Gabaix Granular" residuals as computed in previous study[25]. Here I find that the R squared increases by 40%. Following Gabaix (2011) methodology, one would therefore conclude that 40% of aggregate lending fluctuations are explained by idiosyncratic shocks to big banks.

Then, I control only by the "small banks aggregate shock" and the "'big banks aggregate shock",

[24] Results are robust to defining a constant group of top 50 BHCs throughout the whole sample period, by identifying the top 50 in 2000 for example.

[25] In particular, I control for the logarithm of the size of the banks when extracting the residuals. The following results mean that this is not enough to clean from specific factors affecting the biggest banks.

excluding the granular residual and find that the R-squared also increases by around 40% compared to the case where I control only by the "small banks aggregate shock".

Finally, I run a regression with all 3 controls: the R-squared increases only by 7% compared to the previous specification. This suggests that after controlling for the common factors explaining the biggest BHCs's growth rates, their idiosyncratic shocks is likely to explain only around 7% of aggregate lending fluctuations, a result in line with my findings. This is reassuring as "Gabaix Granular" could still be a good proxy for idiosyncratic shocks hitting the biggest banks, once having controlled for common factors affecting the biggest banks lending growth. All results are presented in panel 2 of table V.

2.7 Robustness Checks

CI Loans Growth Comovement Table VI repeats the previous analysis focusing on CI loans growth covariance and all the results are confirmed. However the POST coefficients are much higher in every of the three columns. It suggests that the rise in lending growth covariance is nearly three times higher when focusing on this category of loans. Compared to the average CI loans growth covariance before the acquisition date of 0.0004, this represents an increases of more than 150%. This suggests that the variance of banking groups' supply shocks is higher than when considering overall loans growth. This is linked to the fact that either at the subsidiary level or at the aggregate level, CI lending fluctuations appear to be more volatile. In particular, the variance of aggregate US CI Loans growth is twice the one of aggregate US Total Loans growth on average on the 1976-2007 period. So the share of aggregate fluctuations explained by BHCs idiosyncratic shocks when focusing on CI or Total Loans growth will be roughly equal. [26]

Heterogeneity Across Banking Groups And Common Factors Affecting All Banking Groups' Subsidiaries In column 1 and 2 of table VII, I test whether or not the results are

[26] This can be seen in equation (6): if one multiplies both the variance of aggregate lending $Var(\frac{\Delta L_t}{L_{t-1}})$ and the variance of idiosyncratic shocks σ^2_{BHC}.

different for acquisitions by the biggest BHCs and the others. Indeed, my interest being on the role of the biggest banking group, it seems legitimate to check if my results are confirmed when focusing on them. To do so, I identify at date the top 50 BHCs in terms of assets in my sample, and I introduce a dummy equal to one if the acquiring BHC belongs to this group on the quarter preceding the acquisition. As indicated in table I, approximatively 25% of all acquisitions are acquisitions by a top BHC. I then interact this dummy with the POST variable, and rerun my baseline specifications. Column 1 and 2 presents my results, with and without time varying controls: the interaction variable is not significant. Therefore, my results seem to hold for acquisitions by both big and smaller BHCs.

In column 3 and 4 of the same table, I test whether or not my results are driven by factors common to all the subsidiaries of BHCs, and only to them as opposed to independent banks. Here the idea is that BHCs may be very specific in the US banking market compared to independent banks. For example, they may be more dependent upon wholesale funding (Demirgüç-Kunt and Huizinga, 2010) , may be more aggressive in their lending policies or more insulated from monetary policies (Campello, 2002). In other words, they may be affected by specific factors, but common to all BHCs, that they transmit to their subsidiaries. In this case, what I observe may not be the transmission to subsidiaries of BHCs idiosyncratic shocks, but only of shocks common to all BHCs which affect similarly all the subsidiaries of all BHCs. This would be an interesting result but would not fit well into the framework I presented before and this would change the conclusions of this paper.

To test this hypothesis, I identify all acquisitions of banks that were already subsidiaries of a BHC before being acquired by another (around 30% of the acquisitions in my sample, as shown in Table I Panel 2). The idea is the following: if the rise in covariance is due to common factors affecting all BHCs, and only the BHCs, the lending growth covariance of any subsidiaries of two different BHCs should be the same. In this case, if one subsidiary of a BHC i is acquired by another BHC k, the lending growth covariance of the newly acquired subsidiary with already owned subsidiaries of BHC k should not increase. To test this hypothesis, I introduce a dummy equal to one for such acquisitions that I interact with the POST variable. Results with and without time varying controls are presented in columns 4 and 5. The interaction variable is negative and significant at the 5 and 10% level. This seems to confirm the fact that all subsidiaries of BHCs are affected by specific factors that induce a higher covariance between them, whether or not they belong to the same BHC, compared to independent banks. However, the coefficient is relatively small: the estimated rise in covariance drops by around 17% compared to table II: such factors seem to only partially explain the results.

Is It Due To A Constant BHC's Effect? A natural question is whether acquiring BHCs change in an homogeneous way the lending growth rate of acquired banks. For example, one might think that acquiring BHCs permanently rise the growth rate of their new subsidiaries through better management or access to internal capital markets. In figure VII, I plot the average difference of Total loans growth of newly acquired banks and the average of Total Loans growth of subsidiaries of the acquiring BHCs that were already owned at the time of acquisition around the acquisition date. The sample is split between acquisitions where the acquired bank' lending growth rate is lower or higher, on average in the two years period preceding the acquisition date, than the average lending growth rate of the acquiring BHC's subsidiaries. One can see that for both types of acquisition, the difference tends to zero after the acquisition date. This suggests that acquiring BHCs do not homogeneously affect the lending growth rates of acquired banks, but rather that common ownership has a homogenizing effect one the lending growth across subsidiaries of the same BHC.

Addressing the Borrower's Base Hypothesis I then try to address an explanation based on a borrowers' effect. The increase of covariance may be due to the fact that the acquiring BHC is expanding in markets similar to the one of the newly acquired bank, which motivates its acquisition. In this case, the rise in covariance may be due to a "'borrowers' effect"'. Under this explanation, the rise in covariance is due to already owned subsidiaries of the BHC expanding on similar markets than the one of the newly acquired one. Being exposed to similar local demand shocks, the lending growth covariance of both group of banks become more similar as time goes by.

One way to test whether or not this drives my results is to compare the lending growth covariance between a newly acquired bank and subsidiaries of the acquiring BHC that are not located in the state of the acquired bank. Indeed, if the covariance rises for these two groups of banks that are operating in different geographical areas this is not likely to be due to local demand shocks effects. [27]

However, the computation of the covariance of these two groups of banks is difficult and very noisy due to a small number of observations (acquisitions where the BHC operates in multiple states). Using covariances, that at are unnormalized statistics highly sensible to outliers, makes the task of working on small samples tenuous. I tried to do so but my results based on test of covariance's change between those two groups are very unstable. I do believe that this is at least partially due to the reasons depicted just before. Hence I present an alternative test that does not require the computation of covariances but that helps me rule out this hypothesis. I run a classic Diff-In-Diff analysis of lending growth comovement, as opposed to a direct test on covariance as in the previous specifications, between the acquired bank j and the others subsidiaries of the acquiring banking group k that are located in another state than j (and that were already owned by k before its acquisition of j). My specification is the following:

$$CG_{j,t} = \alpha_j + \gamma_t + \lambda * \text{BHC SUB AVERAGE}_{j,k,t} + \pi * POST_{j,t} + \beta * POST_{j,t} * \text{BHC SUB AVERAGE}_{j,k,t} + \eta_{j,t} \tag{2.14}$$

The dependent variable $CG_{j,t}$ is the quarterly total loans growth of the acquired bank j. BHC SUB Average$_{j,k,t}$ is the quarterly average of Total loans growth rate among all others subsidiaries of the acquiring BHC k that are located in a state different that the one of the acquired bank and that were already owned by this BHC the quarter preceding the acquisition of j. POST is a dummy equal to one after the acquisition date. β is the coefficient of interest. Following Barberis, Shleifer and Burgel (2005) , or Foucault and Fresard (2014) , the idea is that if the lending growth comovement increases, e.g. if β is positive and statistically significant, this should reflect an increase in the lending growth covariance of the two groups of banks. [28]

[27] I have no data on industry level lending, this is a limitation of the Call Reports. As a consequence, I can not test if the rise in covariance is due to the BHC specializing in lending to some specific industries in which the acquired bank is also specialized in.

[28] More formally, If one considers the following regression, where I drop the date fixed effect :

$$CG_{j,k,t} = \alpha_j + \beta * \text{BHC SUB AVERAGE}_{j,k,t} + \eta_{j,k,t}$$

Table VIII presents the results of the estimation. The β coefficient is significant at the 1% level in the three specifications, including the one in column 3 where I break down the POST dummy into Year To Acquisition dummies that I interact with BHC SUB AVERAGE$_{j,k,t}$. If it is not straigthforward to go from the β coefficients to the value of the average rise in covariance, this tends to prove that the lending growth covariance increases both for subsidiaries in the same state and fot subsidiaries in different states. Hence, this tends to prove that the results are not driven by a pure borrowers' effect as subsidiaries in different states are not likely to share the same local markets. This is because Call Reports data identifies subsidiaries operating in one state only[29] (Michalski and Ors, 2012) .

Partially Adressing the Endogeneity Issue I also run another Diff-In-Diff analysis based on a random "matching" technique that further alleviates the concerns about the endogeneity of the acquisition and the fact that both a borrowers' effect may drive the results. For each acquisition, I randomly pick up a "control" bank located in the same state that the truly acquired bank (the "treated" bank). I further require the control bank to be acquired by another BHC within one year around the acquisition date of the treated bank. I then compute the change in covariance of the lending growth of both the control and the treated banks with subsidiaries of the acquiring BHC of the treated bank. Here again, I focus only on subsidiaries of the acquiring BHC that were already owned by the BHC the quarter before the acquisition of the treated bank. I finally compute the

The β should increase after the acquisition if the covariance of $CG_{j,t}$ and BHC SUB AVERAGE$_{j,k,t}$ increases. More precisely, the probability limit of the OLS estimation of β, following (8) and (9), is:

$$\beta = \begin{cases} \frac{\sigma^2_{agg}}{\sigma^2_{agg}+\sigma^2_{bhc}} & \text{Before the acquisition} \\ \frac{\sigma^2_{agg}+\sigma^2_{bhc}}{\sigma^2_{agg}+\sigma^2_{bhc}} = 1 & \text{After the acquisition} \end{cases}$$

If one includes time fixed effects in the regression, this predicts that the probability limit of the OLS estimation of β, following (8)

$$\beta = \begin{cases} 0 & \text{Before the acquisition} \\ \frac{\sigma^2_{bhc}}{\sigma^2_{bhc}} = 1 & \text{After the acquisition} \end{cases}$$

[29]This changes after the introduction of the Riegle-Neal Act of 1995 who allowed banks to consolidate their subsidiaries across states. As I focus on the pre 1995 period, this is not a concern here.

change in covariances on a 2,3,4 and 5 years windows around the acquisition date for the treated and control banks and run a Diff-In-Diff analysis.

There are two reasons for this test. First, as both banks are in the same state, this can help me further rule out the borrowers' effect hypothesis: if the rise in covariance is due to the fact that the BHC, and its existing subsidiaries, are expanding within the state of the newly acquired bank, their lending growth covariances should also rise with the control bank. Secondly, by choosing a random bank among the ones that will be acquired within one year, I try to partially address endogeneity concern, such as future lending opportunities[30]. Maybe more importantly, this also allows me to rule out an explanation based on a pure "variance effect". Indeed, as covariances are non normalized statistics, the rise in covariance could be due to an increase in the lending growth variance of either the acquired bank or the others subsidiaries of the acquiring BHC following the acquisition date. By including in my control group only banks that are acquired within one year (by another BHC that the one acquiring the treated bank), I can control for any change in variance of acquired banks following their acquisition. In addition, by comparing the treated and control banks with the same set of subsidiaries of the acquiring BHC, I can also control for any effect due to an increase in the variance of the acquiring BHC' others subsidiaries average lending growth.

Regarding the technical part, I keep the same criteria that when computing the covariance in the first part of the paper (I require at least 8 observations whatever the time window) to try to be as transparent as possible. I restrict my sample to acquisitions for which I have non missing covariance change data for both the control and the treated banks. [31]. As a consequence, all my tests are based on a balanced panel. I then compute the average covariance for the control and the matched groups on the 2,3,4 and 5 years before and after the acquisition and run a student's t-test

[30] I do acknowledge that this test is far from perfect, but to date this is my best attempt. The use of finer matching technique, based on past performances and growth, as well as further geographical restrictions (such as the MSA level) to better control for local shocks should be implemented later.

[31] For example, for the 2 years windows, I compute the lending growth covariance with the already owned subsidiaries of the acquiring BHC 2 years before and 2 years after for both the treated and control bank, using each time 8 quarters of lending growth data. I then compute the change in covariance for both the treated and the control banks. I finally keep only the acquisitions for which I have non missing covariance change data for both the treated and the control banks. For the three years window, I compute the 3 years before and 3 years after covariances changes for both banks, using each time 12 quarters of lending growth data, and keep in my sample only acquisitions for which I have non missing covariance change data for the control and the treated banks, etc...

of means comparison, allowing for unequal variances. For the Total Loans and CI Loans growth covariance analysis, I respectively use, on average, 2190 and 1535 acquisitions across the 4 time windows analysis. This is a much smaller sample than the one used in previous analysis which is explained explained mainly by the fact that I require the panel to be strongly balanced and marginally because some of the treated banks have no controls that matched the criteria described previously.

Diff-In-Diff results are presented in table IX for both Total Loans and CI Loans growth covariances and for the 4 time windows. All results are confirmed: the Diff-In-Diffs estimates are all statistically significant at the 1 or 5% level and the point estimate are similar to the ones of tables II and VI.

Risk Sharing And Internal Capital Markets Hypothesis In table X, I turn to another potential explanation: risk sharing trough internal capital markets. Under this hypothesis, the rise in comovement will purely come from the fact that BHCs use internal capital markets to smooth idiosyncratic shocks of each subsidiary, making their lending growths more similar. On the one hand, the literature on banks internal capital markets (Houston, James and Marcus, (1997)) rather suggests that competition for internal funds will lead to a divergence of growth rates between subsidiaries. The idea is that subsidiaries accessing internal funds do it at the expense of the ones that do not (Houston, James and Marcus, (1997), Cremers, Huang and Sautner (2010)) . So this should go against my findings. On the other hand, the literature also shows that a BHC's subsidiary lending growth is very sensitive to its BHC's aggregate cash flows position. This may lead to a convergence of lending growth rates across subsidiaries of the same BHC, each subsidiary lending growth depending on the same BHC aggregate cash flows position. To try to assess whether or not this is driving my results, I follow the literature on banks' internal capital markets and more especially Campello (2002). Following Kashyap and Stein (2000), Campello argues that internal capital markets are more important for small subsidiaries of BHCs than bigger ones as the latest may access external funding more easily. This suggests that the impact of internal capital markets on covariance should be higher for small acquired banks.

I distinguish between acquisition of small and large subsidiaries, the intuition being that covariances should rise more after such acquisitions as small banks are the most likely to be influenced by internal capital markets. First, in the spirit of Campello (2002), I identify all acquisitions of banks that belong to the lowest decile of the Total Loans variable distribution on the quarter preceding the acquisition. I then run my baseline regression including an interaction term POST*SMALL where SMALL is a dummy equal to one if the acquired bank belong to the lowest decile. I report the results in columns 1 and 2 of table X: the interaction terms are all insignificant.

Further Robustness Checks Table XI reports additional robustness checks where I split the sample in two periods (before and after 1987.5, the average date of acquisition)[32], cluster standard errors at the date, state-date and acqui*post levels and restrict the sample to different time windows around the acquisition date. The increase in covariance seem to be higher for the earlier part of the sample. However, this does not qualitatively change the conclusions of this paper.

2.8 Conclusion

In this paper, I ask whether or not big banking groups may impact aggregate lending fluctuations. I show that this is only the case if they homogenize the lending growth between their subsidiaries: if it is not the case, then banking groups are just a collection of small independent banks. I show that one can recover an estimate of the strength of the comovement created by banking groups between their subsidiaries using bank acquisitions and, building on a simple framework, the share of the variance of aggregate lending fluctuations that they may explain. I show that contrary to previous findings, and despite the sharp increase in concentration of the US banking sector over the past decades, the contribution of those shocks to aggregate lending variations is likely to remain small (around 5% of aggregate lending variance). I explain my result by showing that the comovement created by banking groups between their subsidiaries exists but is marginal compared

[32] I also ran regressions including acquisitions made post 1995. All results are unchanged.

to idiosyncratic shocks of those subsidiaries: subsidiaries of large banking groups largely behave as if they were independent from each other.

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Figure 2.1: **Top 5 US Banking Groups' Market Share**

This figure plots the share of total banking assets held by the top 5 US banking groups (BHCs) from 1976 to 2010. *Source:* FED call reports.

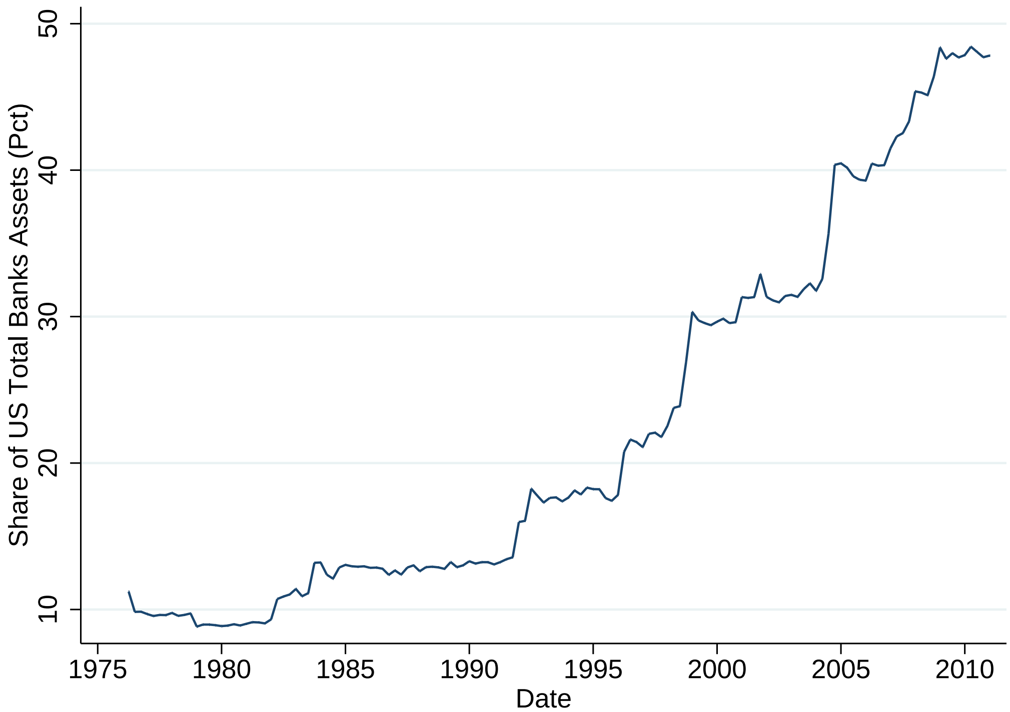

Figure 2.2: **Evolution of US Banking Sector's Herfindhal**

This figure presents the Herfindahl indexes based on total loans for banking group. Total loans are consolidated at the group level. *Source:* FED call reports.

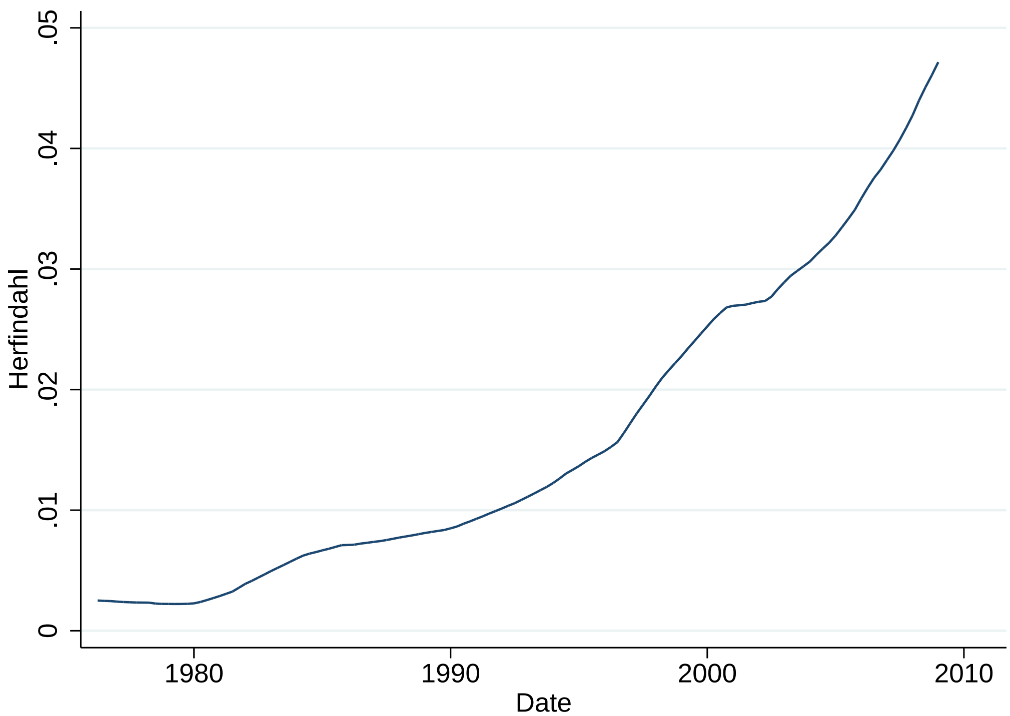

Figure 2.3: **Number of In Sample Acquisitions Per Year**

This figures plots the yearly number of in sample acquisitions. The sample is limited to banks that have been acquired by a BHC in this period following the procedure presented in section 3 and for which I have non missing covariance data on at least 8 quarters over the 10 years period around the acquisition date. *Source:* FED call reports.

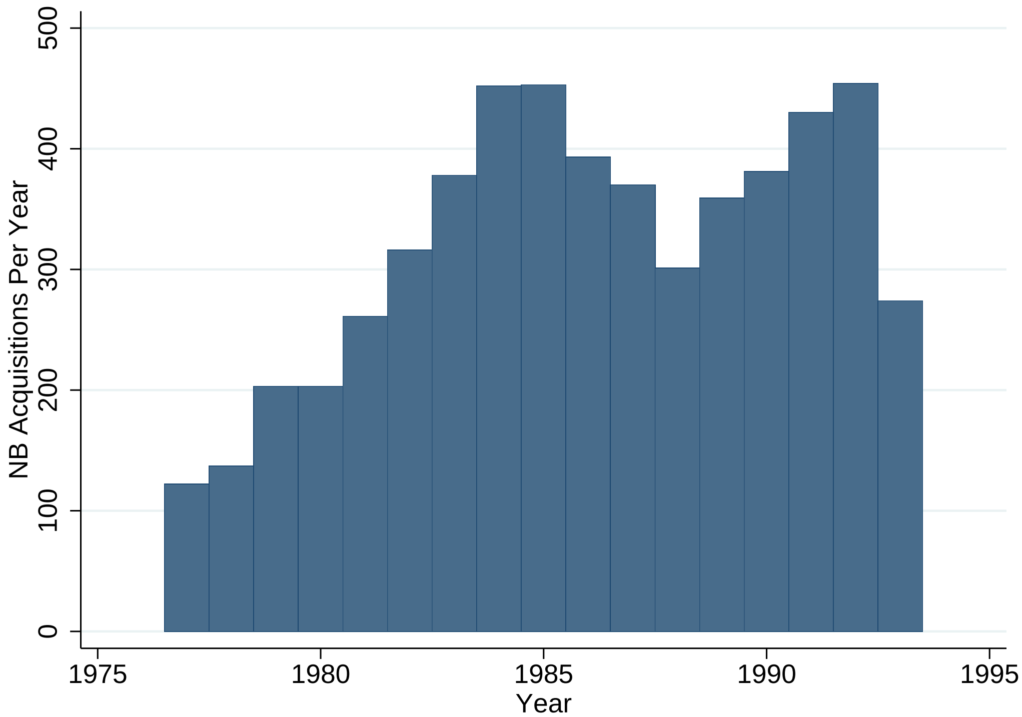

Figure 2.4: **Effect Of Acquisitions On Lending Growth Covariance: A Graphical Illustration**

This figure plots the average covariance of total loans growth between the newly acquired bank and the average total loans growth rate of existing subsidiaries at the time of acquisition from -5 years before the acquisition to 5 years after. The covariance at date t is measured on the 9 quarters around t (4 before, 4 after and t). To net out common shocks effects on the covariance, I then subtract at each date the average covariance for banks that have not yet been acquired. *Source:* FED call reports.

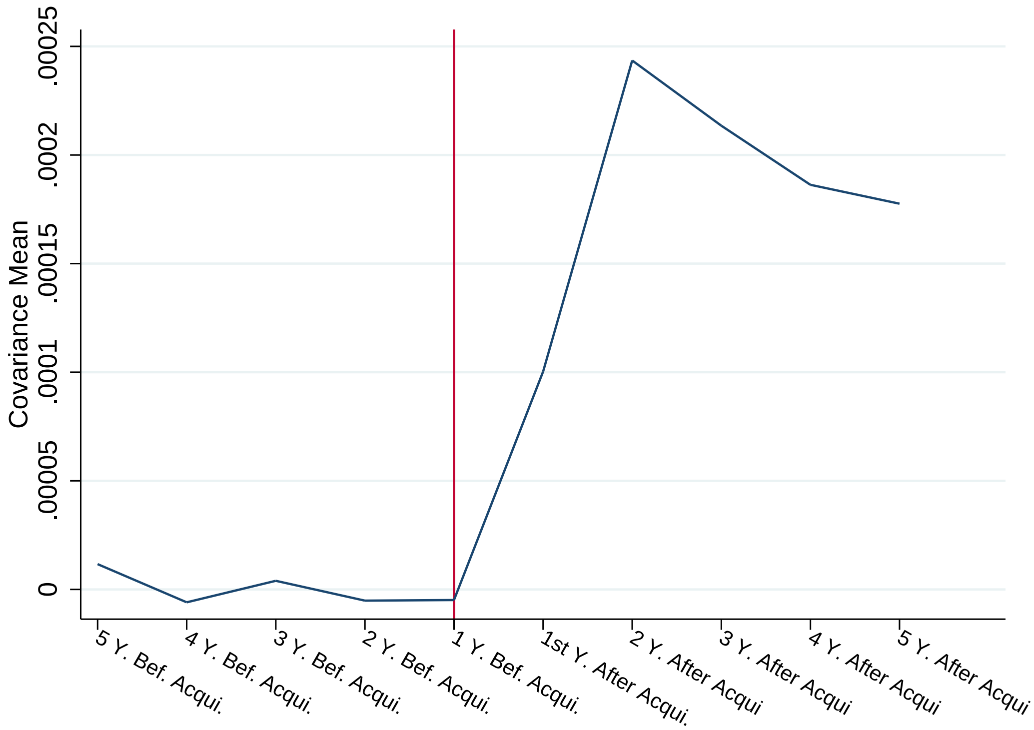

Figure 2.5: **Effect Of Acquisitions On Lending Growth Covariance: Regression Results**

This figures shows the change in lending growth comovement between an acquired bank and the acquiring bank holding company (BHC) others subsidiaries, 4 years before and after the acquisition, 0 being the year of acquisition. I plot the interaction coefficients estimates of the interaction terms $\delta_z * CG_{j,k,t}$ of the following regression: $Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}}) = \alpha_j + \gamma_t + \sum_{z=-3}^{2} \delta_z + \delta_{z>=3} + controls_{j,t} + \eta_{j,t}$. $Cov(LG_{ACQ_{j,k,t}}, LG_{AVGSUB_{k,t}})$ is the quarterly Total Loans growth covariance of the acquired bank with the average Total Loans growth of already owned subsidiaries of the acquiring BHC k. δ_z is a dummy equal to 1 the z_{th} year to acquisition date and 0 otherwise. For example, δ_0 is equal to one for the four quarters following the acquisition, including the acquisition quarter. $\delta_{z>=3}$ is a dummy equal to 1 the $z_{th} >= 3$ years after the acquisition date. I do not include an interaction term for the 5 to 3 years before the acquisition date, so that the reference period is from 5 to 3 years before the acquisition. α_j and γ_t are respectively an acquisition and a date fixed effects. Standards errors are clustered at the acquisition level. *Source:* FED call reports.

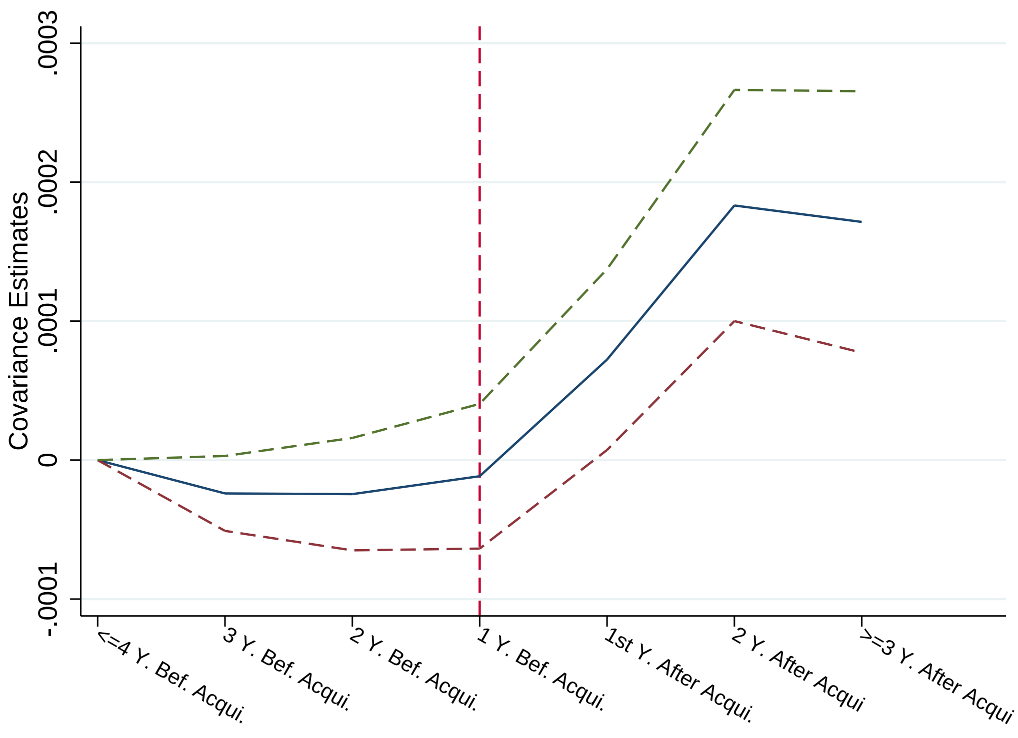

Figure 2.6: **US National Lending Variance Versus Aggregate Shocks Variance**

This figures plots the quarterly value of US national lending variance and aggregate shocks variance. US Total Loans Growth variance is the variance of US national lending growth rate computed on a 5 years centered window. At each quarter, common shocks are defined as being the average total loans growth rate of all US banks in my sample. Their variance at a given quarter is computed on a 5 years centered window. *Source:* FED call reports.

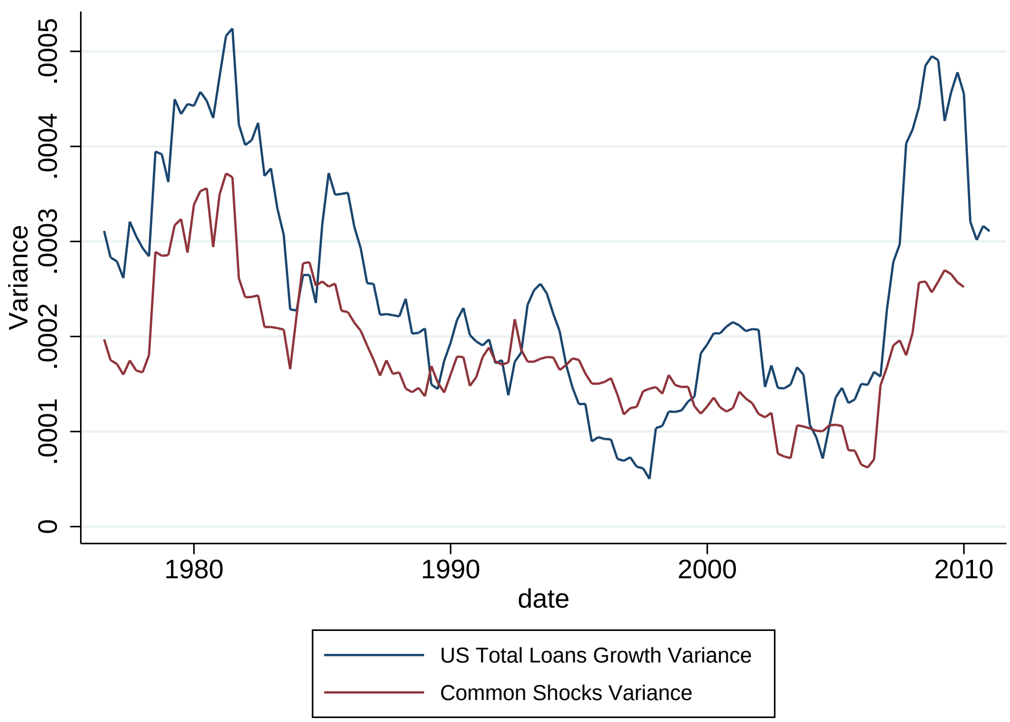

Figure 2.7: **Effect Of Acquisitions On Acquired Banks Lending Growth Rates**

This figure plots the average difference of Total loans growth of newly acquired banks with the average of Total Loans growth of subsidiaries of the acquiring BHCs that were already owned at the time of acquisition. The sample is split between acquisitions where the acquired bank lending growth rate is lower or higher, on average, in the two years period preceding the acquisition date than the average acquiring BHC's subsidiaries lending growth rate. *Source:* FED call reports.

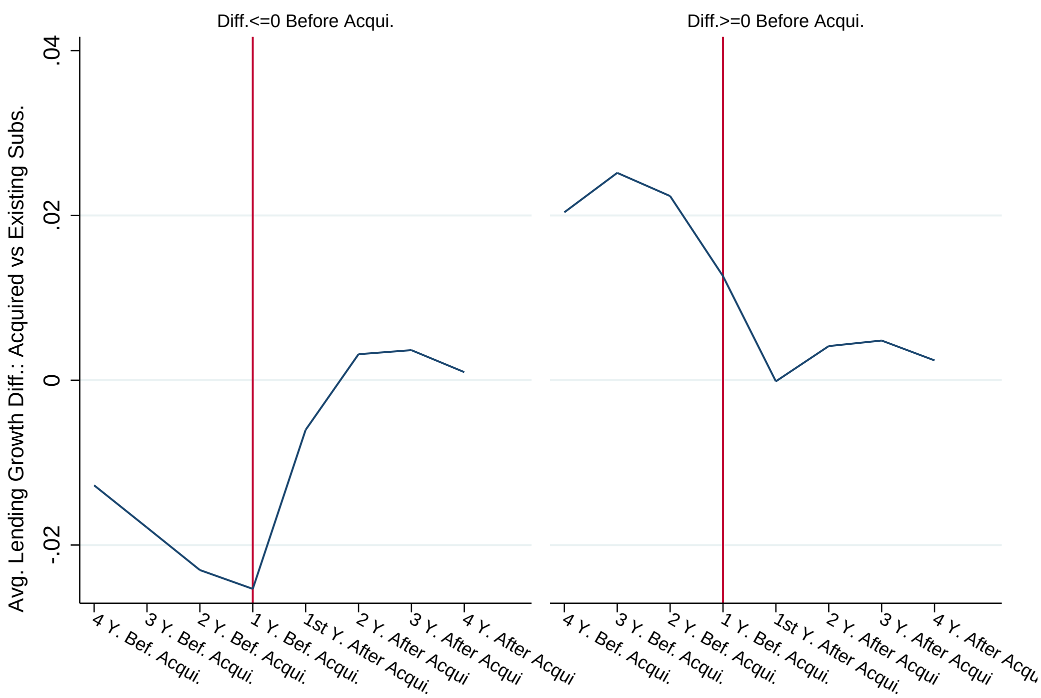

Table 1: Summary Statistics

Note: This table presents summary statistics. Data are from the FED Call reports over the period 1976-1995. The sample is limited to banks that have been acquired by a BHC in this period following the procedure presented in section 3. In Panel A, I give descriptive statistics on acquired banks, the quarter preceding the acquisition. Share of Total Loans to the Real Economy is defined as the ratio of the sum of CI, Real Estate, Agricultural and Loans to Individuals over Total Loans. The BHC subsidiaries variables are the average growth rates on which I compute the covariance. In Panel B, I give descriptive statistics on acquiring BHCs, the quarter preceding the acquisition. Acquiring BHC Number of subsidiaries is the number of subsidiaries of the BHC at the date of acquisition. Acquiring BHC Number of Acquisitions is the number of acquisitions of a given BHC in my sample. In Panel C, I give descriptive statistics on the covariances computed as described in section 3, both before and after the acquisition date, for all quarters in my sample.

Panel A: Bank Level Data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Total Loans (Millions)	62.3	363.3	0.8	16158	4563
Total Loans Growth (Abs)	0.022	0.068	-0.357	0.497	4563
CI Loans Growth (Abs)	0.011	0.147	-0.491	0.499	4358
BHC Subsidiaries Average Total Loans Growth (Abs)	0.035	0.048	-0.437	0.477	4563
BHC Subsidiaries Average CI Loans Growth (Abs)	0.027	0.086	-0.42	0.49	4530
Deposits over Total Assets (Abs)	0.51	0.092	0.006	0.781	4563
Share Loans To Real Econ. (Abs)	0.966	0.05	0.364	1	4563

Panel B: Acquisitions

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Date Merger	1987.8	4.9	1976.5	1997	5487
Acquiring BHC Total Loans (Millions)	3509	7660	2	93267	5487
Acquiring BHC Nb of Acquisitions	24.0	30.9	1	145	5487
=1 if Acquiring BHC in the top 50	0.2	0.4	0	1	5487
From BHC to BHC	0.32	0.47	0	1	5487

Panel C: Covariances

Before/After	**Variable**	**Mean**	**Std. Dev.**	**Variance**	**N**
Before Acquisition	Covariance of Total Loans Growth	0.00033	0.00089	0.00000	66862
Before Acquisition	Covariance of CI Loans Growth	0.0004	0.00396	0.00002	63459
After Acquisition	Covariance of Total Loans Growth	0.00045	0.00098	0.00000	77121
After Acquisition	Covariance of CI Loans Growth	0.00083	0.00429	0.00002	72517

Table 2 : Acquisition and Lending Growth Covariance: Baseline Specification

Note: The dependent variable is the quarterly covariance of Total loans growth of a newly acquired bank j with the average Total Loans growth of subsidiaries of the acquiring BHC k that were already owned by k the quarter before bank j was acquired. Covariances are computed using a 2 years centered window (9 quarters of data) on a ten years window around the acquisition date (5 years before/after). I require that at least 8 non missing values for the covariance computation. POST is the 2 years centered moving average of a dummy equal to 1 for quarters after the acquisition date and 0 otherwise. In the last column, I break down the POST dummy with year to acquisition dummies. I do not include an interaction term for the 5 to 3 years before the acquisition date, so that the reference period is from 5 to 3 years before the acquisition. Time varying controls at the acquired bank level include: the log of total loans as well as the ratio of deposits and equity on total assets. All specifications include date and acquisition fixed effects. Standard errors are clustered at the acquisition level. ***, ** and * mean significant at the 1, 5 and 10 percent confidence level. *Source:* FED call reports.

	(1) Total Loans Gr. Cov.	(2) Total Loans Gr. Cov.	(3) Total Loans Gr. Cov.
POST	0.000233***	0.000232***	
	(8.17)	(8.16)	
$\leq$ 3 Y. Bef. Acqui.			-0.0000243*
			(-1.77)
2 Y. Bef. Acqui.			-0.0000249
			(-1.20)
1 Y. Bef. Acqui.			-0.0000121
			(-0.45)
1st Y. After Acqui.			0.0000706**
			(2.12)
2 Y. After Acqu.			0.000183***
			(4.30)
$\geq$ 3 Y. After Acqu.			0.000172***
			(3.57)
Acquisition FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Observations	143983	143983	143983
R-Squared	0.351	0.351	0.351

t statistics in parentheses

Table 3: Estimating The Contribution To Aggregate Fluctuations Of BHC's Idiosyncratic Shocks

Note: This table presents the main results of this paper: the potential contribution of big BHC's idiosyncratic shocks to US aggregate lending growth variance for different periods. It is calculated as the product of the average Herfindhal index of the banking sector over the period times the estimated variance of BHC's idiosyncratic shocks divided by the variance of US aggregate lending growth on the period ($\frac{\text{Estimated BHC Idio. Shocks Variance *Average HHI BHCs}}{\text{US Total Loans Growth Variance}}$). *Source:* FED call reports.

Estimated Banking Groups Shocks Variance	0.00023
US Total Loans Growth Variance 1976-1995	0.0005
US Total Loans Growth Variance 1995-2007	0.0001
US Total Loans Growth Variance 2000-2010	0.0003
Average Banking Market Herfindhal 1976-1995	0.0065
Average Banking Market Herfindhal 1995-2007	0.0264
Average Banking Market Herfindhal 2000-2010	0.0366
Share Of Variance Explained By BHCs' Idio. Shocks 1976-1995 (Pct)	0.3%
Share Of Variance Explained By BHCs' Idio. Shocks 1995-2007 (Pct)	4.5%
Share Of Variance Explained By BHCs' Idio. Shocks 2000-2010 (Pct)	2.7%

Table 4: Interpreting The Results: The Relative Explanatory Power of BHC Idiosyncratic Shocks

Note: In this table the dependent variable is the quarterly total loans growth rate of a BHC's subsidiary. The sample is restricted to the period 1976-1995 and to subsidiaries of BHCs (I exclude independent banks). "'Aggregate shocks"' is the average of all subsidiaries total loans growth rate on a given date. "'Local shocks"' is the average growth rates of all subsidiaries in a given state a date t (excluding the observation growth rate). "'BHC idiosyncratic shocks"' is the average growth rate on a given date of all others subsidiaries of a subsidiary's BHC. "' Local BHC idiosyncratic shocks"' is the same variable limited to the subsidiaries located in the same state than the observation. The increase in the number observations is due to the fact that I no longer restrict the sample to observations around the acquisition date. *Source:* FED call reports.

	Subsidiary FE	Adding Different Type Of Shocks			
	(1)	(2)	(3)	(4)	(5)
		Aggregate	Local	BHC	BHC's Local
Aggregate Shocks		1.092***	0.245***	0.193***	0.201***
		(102.03)	(13.61)	(11.49)	(12.59)
Local Shocks			0.830***	0.540***	0.361***
			(49.46)	(33.25)	(23.44)
BHC Idio. Shocks				0.325***	0.222***
				(42.18)	(29.04)
Local BHC Idio. Shocks					0.0208***
					(32.71)
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	187710	187710	187710	187710	187710
R-Squared	0.0815	0.172	0.220	0.254	0.280

t statistics in parentheses

Table 5: Explaining The Differences With Previous Findings: Omitted Variable Bias

Note: In Panel 1, the dependent variable is the quarterly aggregate loans growth rate of US top 50's BHCs. In Panel 2, the dependent variable is the quarterly US aggregate loans growth rate. In panel 1 and 2, "'Small Banks Aggregate Shock"' is the average total loans growth rates of all in sample banks except the top 50 ones and "'Big Banks Aggregate Shock"' is the average total loans growth rates of the top 50 banks. In panel 2, "'Granular Residuals"' is basically the total loans weighted average of the difference between the average growth rate of all banks in a quarter and a given bank growth rate. Total loans are consolidated at the BHC level in both panels. Regressions are ran on the 1975-2010 period. *Source:* FED call reports.

Panel 1: Identifying Big Banks Specific Shocks

	(1)	(2)
	Small Banks Aggregate Shock Only	Adding the Big Banks Aggregate Shock
Small Banks Aggregate Shock	0.641***	-0.209***
	(6.33)	(-2.62)
Big Banks Aggregate Shock		1.057***
		(16.10)
Observations	139	139
R-Squared	0.226	0.734

t statistics in parentheses

Panel 2: Quantifying the Omitted Variable Bias

	A la Gabaix Method		Omitted Variable Bias	
	(1)	(2)	(3)	(4)
Small Banks Aggregate Shock	0.753***	0.918***	0.176***	0.707***
	(10.78)	(25.95)	(3.11)	(9.72)
Granular Residual		1.166***		0.901***
		(20.67)		(9.22)
Big Banks Aggregate Shock			0.718***	0.215***
			(15.40)	(3.28)
Observations	139	139	139	139
R-Squared	0.459	0.869	0.803	0.879

t statistics in parentheses

Table 6: Robustness test: CI Loans Growth Covariance

Note: The dependent variable is the quarterly covariance of CI loans growth of a newly acquired bank j with the average Total Loans growth of subsidiaries of the acquiring BHC k that were already owned by k the quarter before bank j was acquired. Covariances are computed using a 2 years centered window (9 quarters of data) on a ten years window around the acquisition date (5 years before/after). I require that at least 8 non missing values for the covariance computation. POST is the 2 years centered moving average of a dummy equal to 1 for quarters after the acquisition date and 0 otherwise. In the last column, I break down the POST dummy with year to acquisition dummies. I do not include an interaction term for the 5 to 3 years before the acquisition date, so that the reference period is from 5 to 3 years before the acquisition. Time varying controls at the acquired bank level include: the log of total loans as well as the ratio of deposits and equity on total assets. All specifications include date and acquisition fixed effects. Standard errors are clustered at the acquisition level. ***, ** and * mean significant at the 1, 5 and 10 percent confidence level. *Source:* FED call reports.

	(1)	(2)	(3)
	CI Loans Cov.	CI Loans Cov.	CI Loans Cov.
POST	0.000657***	0.000657***	
	(4.89)	(4.89)	
$\leq$ 3 Y. Bef. Acqui.			-0.0000726
			(-1.10)
2 Y. Bef. Acqui.			-0.0000936
			(-0.93)
1 Y. Bef. Acqui.			-0.0000741
			(-0.57)
1st Y. After Acqui.			0.000160
			(0.99)
2 Y. After Acqu.			0.000483**
			(2.32)
$\geq$ 3 Y. After Acqu.			0.000520**
			(2.20)
Acquisition FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Observations	135976	135976	135976
R-Squared	0.267	0.267	0.267

t statistics in parentheses

Table 7: Robustness Test: Big versus Others BHCs and Acquisitions from BHCs to BHCs

Note: The dependent variable is the quarterly covariance of Total loans growth of a newly acquired bank j with the average Total Loans growth of subsidiaries of the acquiring BHC k that were already owned by k the quarter before bank j was acquired. Covariances are computed using a 2 years centered window (9 quarters of data) on a ten years window around the acquisition date (5 years before/after). I require that at least 8 non missing values for the covariance computation. POST is the 2 years centered moving average of a dummy equal to 1 for quarters after the acquisition date and 0 otherwise. TOP is a dummy equal to one is the acquiring BHC belonged to the top 50 BHCs in terms of assets the quarter preceding the acquisition date. BHC TO BHC is a dummy equal to one if the acquired bank was already a subsidiary of another BHC, as opposed to being an independent bank the quarter preceding the acquisition. Time varying controls at the acqured bank level include: the log of total loans as well as the ratio of deposits and equity on total assets. All specifications include date and acquisition fixed effects. Standard errors are clustered at the acquisition level. ***, ** and * mean significant at the 1, 5 and 10 percent confidence level. *Source:* FED call reports.

	(1)	(2)	(3)	(4)
	Top BHCs	Top BHCs	BHC to BHC	BHC to BHC
POST	0.000236***	0.000235***	0.000250***	0.000250***
	(7.82)	(7.80)	(8.03)	(8.02)
POST*TOP	-0.0000167	-0.0000139		
	(-0.49)	(-0.41)		
POST*BHC To BHC			-0.0000620**	-0.0000616*
			(-1.97)	(-1.95)
Acquisition FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	143983	143983	143983	143983
R-Squared	0.351	0.351	0.351	0.351

t statistics in parentheses

Table 8 Robustness Test: Ruling out the Borrowers base hypothesis

This table presents the results of the following regression: $CG_{j,t} = \alpha_j + \gamma_t + \text{BHC SUB AVERAGE}_{j,k,t} + POST_{j,t} + POST_{j,t} * \text{BHC SUB AVERAGE}_{j,k,t} + controls_{jt} + \eta_{jt}$. The dependent variable $CG_{j,t}$ is the quarterly total loans growth of the acquired bank j. BHC SUB Average$_{j,k,t}$ is the quarterly average of Total loans growth rate among all others subsidiaries of the acquiring BHC k that are located in a state different that the one of the acquired bank and that were already owned by this BHC the quarter preceding the acquisition of j. POST is a dummy equal to one after the acquisition date. In the last column, I break down the POST dummy with year to acquisition dummies. I do not include an interaction term for the 5 to 3 years before the acquisition date, so that the reference period is from 5 to 3 years before the acquisition. Time varying controls at the acquired bank level include: the log of total loans as well as the ratio of deposits and equity on total assets. All specifications include date and acquisition fixed effects. Standard errors are clustered at the acquisition level. ***, ** and * mean significant at the 1, 5 and 10 percent confidence level.*Source:* FED call reports.

	(1) Out Of States Subs.	(2) Out Of States Subs.	(3) Out Of States Subs.
Subs. Avg. GR	0.0311***	0.0332***	0.0228*
	(3.41)	(3.75)	(1.73)
POST	-0.00144	-0.00267*	
	(-0.89)	(-1.71)	
POST*Subs. Avg. GR	0.0961***	0.0911***	
	(4.76)	(4.57)	
$\leq$ 3 Y. Bef. Acqui.*Subs. Avg. GR			-0.0204
			(-1.00)
2 Y. Bef. Acqui.*Subs. Avg. GR			0.0192
			(0.96)
1 Y. Bef. Acqui.*Subs. Avg. GR			0.0322*
			(1.68)
1st Y. After Acqui.*Subs. Avg. GR			0.0886***
			(2.94)
2 Y. After Acqu.*Subs. Avg. GR			0.155***
			(4.61)
$\geq$ 3 Y. After Acqu.*Subs. Avg. GR			0.0946***
			(2.87)
Acquisition FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Observations	51476	51476	51476
R-Squared	0.183	0.222	0.225

t statistics in parentheses

Table 9: Robustness Test: Using a Randomly Matched Sample of Treated and Controls Banks

In this table, I run Diff-In-Diffs analysis of the change in lending growth covariance between a newly acquired bank j and subsidiaries of the acquiring BHC k that were already owned by k the quarter before bank j was acquired, using a randomly matched control group. To each bank j acquired by a BHC k (the treated bank), I randomly assign a control bank. I require the control bank to be located in the same state as bank j and to be acquired by another BHC than k within one year around the acquisition date of bank j. I then compute, for both the treated and the control banks separately, the change in covariance of their Total loans growth with the average Total Loans growth of subsidiaries of the acquiring BHC k that were already owned by k the quarter before bank j was acquired before and after the acquisition date of bank j on a 2,3,4 and 5 years time windows. I therefore compare the change in lending growth covariance of the control and treated banks with the same set of subsidiaries before and after the acquisition date of j. I finally run a Diff-In-Diffs analysis of the change in covariance for each of these time windows by comparing the average change in covariance among the treated and the control banks. For all analysis I require the panel to be balanced,e.g. , I keep only acquisitions for which I have non missing covariance change data both for the treated and control banks. Panel A and B respectively present the results for the Total and CI Loans growth. *Source:* FED call reports.

Panel A: Total Loans Growth

	Avg. Acquired Banks Covariance Change	Avg. Control Banks Covariance Change	Diff-In-Diffs (Acquired Vs Controls)	Nb . Obs	Nb Acqui.
2 Y. Before/After	.0001731***	.41e-06	.0001717***	3520	1760
	(5.9)	(0.05)	(4.2)		
3 Y. Before/After	.0001834***	.0000102	.0001732***	4722	2361
	(7.6)	(0.5)	(5.4)		
4 Y. Before/After	.0001953***	.0000102	.0001851***	4656	2328
	(8.7)	(0.5)	(6.1)		
5 Y. Before/After	.000237***	4.30e-06	.0002327***	4624	2312
	(10.7)	(0.2)	(7.8)		

Panel B: CI Loans Growth

	Avg. Acquired Banks Covariance Change	Avg. Control Banks Covariance Change	Diff-In-Diffs (Acquired Vs Controls)	Nb Obs.	Acqui.
2 Y. Before/After	.0004217**	-.0001568	.0005785**	1268	634
	(1.9)	(-0.8)	(2.0)		
3 Y. Before/After	.000539***	-.000051	.00059***	3756	1878
	(4.4)	(-0.4)	(3.5)		
4 Y. Before/After	.0006301***	-.0000535	.0006835***	3678	1839
	(5.7)	(-0.5)	(4.6)		
5 Y. Before/After	.0005993***	.0000198	.0005796***	3584	1792
	(5.4)	(0.2)	(3.9)		

Table 10: Robustness Test: Internal Capital Market Hypothesis

Note: The dependent variable is the quarterly covariance of Total loans growth of a newly acquired bank j with the average Total Loans growth of subsidiaries of the acquiring BHC k that were already owned by k the quarter before bank j was acquired. Covariances are computed using a 2 years centered window (9 quarters of data) on a ten years window around the acquisition date (5 years before/after). I require that at least 8 non missing values for the covariance computation. POST is the 2 years centered moving average of a dummy equal to 1 for quarters after the acquisition date and 0 otherwise. SMALL is a dummy equal to one if the acquired bank belong to the lowest decile in term of the Total Loans variable the quarter preceding the acquisition. SMALL BHC TO BHC is a dummy equal to 1 if the acquired bank belong to the lowest decile and is a subsidiary of a BHC at the time of acquisition. Time varying controls at the acquired bank level include: the log of total loans as well as the ratio of deposits and equity on total assets. All specifications include date and acquisition fixed effects. Standard errors are clustered at the acquisition level. ***, ** and * mean significant at the 1, 5 and 10 percent confidence *Source:* FED call reports.

	(1) SMALL	(2) SMALL	(3) BHC To BHC	(4) BHC To BHC
POST	0.000222***	0.000222***	0.000232***	0.000232***
	(7.73)	(7.73)	(8.07)	(8.07)
POST*SMALL	0.0000980	0.0000967		
	(1.35)	(1.33)		
POST*SMALL SMALL BHC TO BHC			0.0000295	0.0000289
			(0.25)	(0.25)
Acquisition FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	143983	143983	143983	143983
R-Squared	0.351	0.351	0.351	0.351

t statistics in parentheses

Table 11: Robustness Test: Others

The dependent variable is the quarterly covariance of Total loans growth of an acquired bank j with the average Total Loans growth of already owned subsidiaries of the acquiring BHC k. Covariances are computed on a 2 years centered window (9 quarters of data) on a ten years window around the acquisition date (5 years before/after). I require that at least 8 non missing values for the covariance computation. POST is the 2 years centered moving average of a dummy equal to 1 for quarters after the acquisition date and 0 otherwise. In panel A, I split the sample period in 1987.5 (the average acquisition date). In panel B, I test different clustering levels. In panel C column 1,2 and 3 I respectively restrict my sample to observations within a 2,3 and 4 years period around the acquisition date. Time varying controls at the acquired bank level include: the log of total loans as well as the ratio of deposits and equity on total assets. All specifications include date and acquisition fixed effects. Standard errors are clustered at the acquisition level. ***, ** and * mean significant at the 1, 5 and 10 percent confidence level. *Source:* FED call reports.

Panel A: Splitting the Sample Period

	(1) All Sample	(2) Before 1987.5	(3) After 1987.5
POST	0.000232***	0.000297***	0.000185***
	(8.16)	(7.51)	(4.53)
Acquisition FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	143983	84841	62015
R-Squared	0.351	0.363	0.536

t statistics in parentheses

Panel B: Using Different Clustering Level

	(1) Post*Acqui Cluster	(2) Date Cluster	(3) State-Date Cluster
POST	0.000232***	0.000232***	0.000232***
	(10.87)	(10.36)	(13.89)
Acquisition FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	143983	143983	143983
R-Squared	0.351	0.351	0.351

t statistics in parentheses

Panel C: Varying Time Windows Around The Acquisition Date

	(1) 2 Y. Around Acqui	(2) 3 Y. Around Acqui	(3) 4 Y. Around Acqui
POST	0.000246***	0.000238***	0.000268***
	(5.05)	(6.40)	(8.21)
Acquisition FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	59740	86431	110275
R-Squared	0.542	0.455	0.407

t statistics in parentheses

Chapter 3

The Transmission of Corporate Risk Culture

Joint with Thomas Bourveau (HKUST) and Adrien Matray (Princeton University)

3.1 Introduction

This paper examines how corporate culture affects managers' discretionary choices of risk assessment in the banking industry. The prevalent opinion among business press, regulators and scholars is that inadequate culture is often to blame in large corporate scandals. Indeed, "limit pushing values" and lack of monitoring processes have been cited as contributing factors in the Enron case.[1] Similar critiques applied to the recent crisis in the financial industry. For example, Nobel Laureate Robert J. Shiller identified corporate culture, which he refers to as "the spirit of the times" has one of the driving forces behind the 2008-2009 financial crisis. In line with this statement, Fahlenbrach et al. (2012) find indirect evidence that persistence in banks' risk culture explains their performance during the recent crisis.

Despite such criticisms, the empirical literature in accounting, economics and finance has not been able to fully quantify the role played by corporate culture in order to understand firm policies. The lack of empirical results can be explained partly by the challenge of carefully observing and quantifying corporate culture across organizations.[2] The central contribution of this paper is to develop an empirical model to identify plausibly exogenous changes in corporate culture and test whether such changes explain variations in managers' discretionary choices in the context of risk assessment.

Corporate culture has been defined in various ways. The organization theory literature defines corporate culture as a specific set of rules, norms, values, beliefs, and preferences shared within an organization, which guide employees by defining appropriate behavior for various situations (Schein, 1983; Ravasi and Schultz, 2006). It has long been recognized that both formal rules pertaining to control systems and informal organizational features, including values and beliefs, are part of firms' culture (e.g., Johnson, 1988). In economic theory, the importance of corporate culture stems from contract incompleteness (Grossman and Hart, 1986). In this context, corporate culture helps agents within firms to deal with situations with multiple equilibria (Kreps, 1990). In this paper, we refer

[1] See, for example, the article entitled "At Enron, Lavish Excess Often Came Before Success", published in the Wall Street Journal on February 26, 2002.

[2] We acknowledge that there is a vast literature in the social sciences examining the role of corporate culture in organizations. We review this literature in Section 2.

to corporate culture as all types of rules, either formal or informal, explicit or tacit, used in an organization to shape agents' behavior.

We focus on corporate culture in the context of the banking industry and examine one dimension that is particularly likely to be subject to corporate culture: discretionary risk assessment, measured using loan loss provisions (LLPs, hereafter). Loan loss provisions are non-cash expenses that represent a bank's estimate of *future* loan losses. Such provisions are important because they are associated with banks' risk-taking profiles Bushman and Williams (2012, 2015). Since there is no single way to estimate these provisions, managers' subjectivity is likely to be influenced by the rules, norms and preferences embedded in an organization. Indeed, prior accounting studies establish that there is significant heterogeneity across banks in the timeliness and accuracy of their LLPs (e.g., Liu and Ryan, 1995, 2006). Furthermore, prior studies also show that banks use reporting discretion in LLPs for various reasons, including circumventing capital adequacy requirements or smoothing earnings.[3] As a result, LLPs, which represent the largest accrual in a bank's financial statement constitute a well-suited corporate outcome to examine in the context of transmission of corporate culture.

To identify the impact of corporate culture on banks' discretionary choices in the context of risk assessment, we rely on banking groups' acquisitions of new banking subsidiaries. Specifically, we develop and use a difference-in-differences design to test whether the comovement in loan loss provisioning between a newly acquired subsidiary and the existing subsidiaries of the acquiring banking group increases *after* the acquisition date. If the acquiring group is able to impose its risk-assessment culture on the target bank, we expect the LLPs of the target bank to follow that of the acquiring bank more closely after the acquisition is completed. Again, in our setting, corporate culture encompasses both formal credit risk modeling tools and informal norms and values related to risk assessment practices within an organization.

We retrieve bank balance-sheet data using the FED Call Reports database and identify 4,585 changes in ultimate ownership for U.S. banks over the 1976 - 2005 period. We restrict our sample

[3] Beatty and Liao (2014) provide a survey of the research on banks' financial accounting. Specifically, their Section 5 reviews the literature on banks' financial reporting discretion and capital and earnings management.

to the pre-2005 period to avoid capturing the effect of the financial crisis on credit losses and the increased uncertainty about future loan defaults.

Using our empirical model, we first establish that the comovement in LLPs between the target and the banking group increases after the acquisition date and that the effect is permanent. In our regression specifications, we control for a number of bank and state characteristics that have been shown in the literature to affect LLPs and that could plausibly affect the acquisition decision as well. We further corroborate our findings by adding various sets of fixed effects to our model. In the most stringent specification, we remove any unobserved time-varying heterogeneity across states by adding state-year fixed effects.[4] Moreover, we find that the increase in comovement does not precede the acquisition itself. This rules out the endogeneity concern and suggests that our results are driven by the transmission of culture within banking groups rather than by banking groups selecting targets whose discretionary behavior is already similar *ex ante* to that of the group.

We next extend our analysis by following Angrist and Krueger (2001), who argue that most exogenous shocks have a heterogeneous effect across affected subjects. We conduct two sets of cross-sectional tests. First, we predict and find that our effect is more pronounced when the acquiring and target banks are located in the same metropolitan area. This finding is consistent with the literature in economic geography arguing that the transmission of knowledge across firms and the ability to influence peers are enhanced by geographic proximity.[5]

Second, we partition our sample based on the ability of an acquirer to plausibly influence the behavior of its target and find that greater bargaining power amplifies the effect. Using relative size as a proxy for bargaining power, we find that our effect is smaller when the size of the target is relatively large compared to that of the acquiring bank. This finding is consistent with previous studies in the M&A literature arguing that larger size serves as an effective takeover defense (e.g.,

[4]This set of fixed effects ensures that we remove any change in regulation and/or macroeconomic shocks at the state level that may affect both the number of bank acquisitions and the comovement in LLPs. We use state-year fixed effects because, as shown by Gormley and Matsa (2014), using the average effects estimator where the dependent variable is manually demeaned produces a biased estimate.

[5]The notion of geographic proximity is central in the agglomeration economic literature and innovation literature studying "knowledge spillovers". For surveys, see, for example, Audretsch and Feldman (2004) and Carlino and Kerr (2014). In the banking literature, a recent study by Gaspar (2015) provides plausibly causal evidence that a reduction in distance between a bank's headquarters and its subsidiaries improves the monitoring of the subsidiaries, which translates into higher performance.

Masulis et al., 2007). This result is also in line with experimental studies that document the existence of post-merger cultural clashes when the size of the two merging entities is comparable (e.g., Weber and Camerer, 2003).

Finally, we acknowledge that acquired banks may systematically differ from non-acquired ones, and that some remaining unobservable characteristics may drive our results. That is, it might be that some unknown factors driving the acquisition decision might lead the LLPs of the target and acquiring banks to comove more even in the absence of the acquisition. To account for this endogeneity concern, we use a matching technique. Specifically, we match each acquired bank in our sample with another non-acquired bank to create a control group of placebo target banks using Mahalanobis matching.[6] Our analysis reveals that the comovement in LLPs between our group of placebo target banks and acquiring banking groups does not increase around the placebo acquisition date. This reduces the risk that our results are driven by banks' characteristics in the pre-acquisition period.

Our paper is related to three strands of literature. First, we contribute to the literature on the role of corporate culture in organizations, while prior studies focus mostly on the role of national culture, including in M&A settings (Ahern et al., 2012). Recent studies started to quantify how corporate culture is associated with corporate policies and firm characteristics (Cronqvist et al., 2009; Popadak, 2014; Guiso et al., 2015). Our paper innovates along two main dimensions. First, our design allows us to make a plausible causal claim and document that corporate culture is transferred from acquiring groups to target banks.[7] Importantly, we find that the change in behavior does not precede the change in ownership, which plausibly suggests that we capture changes in culture that occurred after the acquisition. Second, we concentrate our analysis on the transmission of corporate culture in financial institutions. Thus, our findings also relate to the growing literature investigating banks' characteristics during the recent financial crisis, including managers'

[6] We require our matched control bank to be located in the same state as the one that is actually acquired and then match on observable characteristics in the year of the acquisition. We discuss our approach in further detail in Section 6.

[7] In a related study, Fisman et al. (2015) provide causal evidence that cultural proximity between bank officers and borrowers improves the efficiency of credit allocation. However, their study examines cultural proximity between contracting parties, while our paper focuses on corporate culture. Therefore, our paper is to our knowledge the first one to make a plausible causal claim regarding the effect of corporate culture on firms' decisions.

compensation and risk incentives (Fahlenbrach and Stulz, 2011; Cheng et al., 2014). Other studies find indirect evidence that corporate culture may explain banks' performance sensitivity to economic crises (Fahlenbrach et al., 2012) and that a common profit-oriented corporate culture affects employees across multiple activities within financial institutions (Pacelli, 2015).

Second, our findings contribute to the accounting literature that examines the determinants of managers' discretionary choices regarding LLPs. Prior studies document that bank managers use the discretion allowed within accounting standards in their LLPs to manage their reported regulatory requirements (Moyer, 1990; Beatty et al., 1995; Collins et al., 1995) and that this behavior is concentrated in the pre-Basel period (e.g., Ahmed et al., 1999). Other studies specifically examine the use of discretion in LLPs for earnings management incentives to avoid a decrease in reported earnings (Beatty et al., 2002). Our findings highlight that the transmission of corporate culture through acquisitions explains part of banks' observed heterogeneity in their loan loss provisioning.

Third, our paper relates to the literature studying the consequences of bank mergers. Regarding prices, researchers have documented the unfavorable effects of increased market concentration on deposit rates (Prager and Hannan, 1998), consumer loan rates (Kahn et al., 2005), real-estate loan rates (Garmaise and Moskowitz, 2006) and commercial and industrial loan rates (Sapienza, 2002; Erel, 2011). The effects of market concentration on efficiency in the financial sector are more nuanced (e.g., Jayaratne and Strahan, 1998; Karceski et al., 2005; Hombert and Matray, 2014).

The rest of the paper is organized as follows. We review the literature and develop our hypotheses in Section 2. Section 3 describes the data sources and variables. In Section 4, we present our empirical strategy. In Section 5, we report our main findings. Robustness tests are discussed in Section 6. Section 7 concludes.

3.2 Hypothesis Development

Corporate culture is often described by practitioners as an underestimated key factor in organizational succes.[8] In particular, scholars have pointed out the role of culture in mergers and acquisitions (Nahavandi and Malekzadeh, 1988; Morosini et al., 1998; Bargeron et al., 2012). In this paper, we do not attempt to relate features of corporate culture to firms' decisions. Instead, we explore how corporate culture is transmitted from acquiring to target banks, and under which circumstances this transmission is enhanced.

Corporate culture has been defined in various ways, and the absence of a unified definition stems from the challenge of precisely quantifing all aspects of corporate culture. Formally, economic theory defines corporate culture as a tool to help agents within firms to deal with situations with multiple equilibria (Kreps, 1990; Hermalin, 2001). In this paper, we label as corporate culture all types of formal and informal guidance that influence employees' behavior. This definition includes both formal control systems and informally shared values or beliefs and is derived from the Competing Values Framework developed in the organization theory literature (e.g., Quinn and Rohrbaugh, 1983; Quinn and Cameron, 1983). This particular framework has been used recently by Thakor (2015) in his review of the literature on corporate culture and its application to the financial sector.

[8] For example, see http://www.greatplacetowork.com/publications-and-events/blogs-and-news/2430-you-cant-legislate-a-smile.

The common challenge to empirical studies is that corporate culture is difficult to quantify in systematic ways for a large sample of firms. Prior studies have opted for various solutions to examine the role of corporate culture. Early studies aimed at assessing variations in culture across organizations often use cross-country comparisons (Hofstede et al., 1983). Other researchers choose to use detailed within-organization case studies (e.g., Larcker and Tayan, 2015). For larger samples of firms, prior studies usually rely on two types of construct to quantify corporate culture. A first set of articles relies on observable CEO characteristics to proxy for the strength of a firm's ethical values and relates this feature to various corporate outcomes such as financial fraud. These characteristics include, for example, suspect options backdating (Biggerstaff et al., 2015), managers' taste for luxury products and their prior legal infractions (Davidson et al., 2015), and CEO military experience (Benmelech and Frydman, 2015). A second set of studies quantifies corporate culture across firms using surveys. For example, Guiso et al. (2015) use a novel dataset based on extensive surveys of the employees of approximately 1,000 U.S. firms developed by the Great Place to Work Institute. Next, they correlate the strength or features of corporate culture to firms' characteristics.

The strength of the studies using surveys and/or CEO characteristics is that they quantify one aspect or several aspects of a firm's culture over large enough samples to use econometric tools. The drawback of this approach is that it does not account for the endogenous relationship between a firm's culture and other corporate characteristics.[9] In this paper, we adopt a novel approach and develop an empirical model to account for the endogenous relationship between corporate culture and firm policies. That is, instead of quantifying corporate culture for an organization in a given year, we use bank acquisitions as a unexpected change in corporate culture for newly acquired banks. We next examine whether the culture of the acquiring bank in terms of risk assessment is transmitted to the acquired bank.[10]

[9]One exception is the study by Benmelech and Frydman (2015) that exploits exogenous variation in the propensity to serve in the military as an instrument for CEO traits.

[10]We acknowledge that the choice of the target bank is unlikely to be random. In section 5, we provide evidence that target banks are not selected because they exhibit behavior similar to their future parent company's before the acquisition. In section 6, we run additional tests to rule out the risk that our effects primarily reflect a selection problem.

Practitioners and scholars have stressed that the process of cultural transfer from acquiring to target companies (i.e., acculturation) is part of firms' post-acquisition integration plans. However, the ability of an acquiring firm to transfer its culture remains unclear. Indeed, prior studies in organization behavior document strong resistance to acculturation processes (e.g., Nahavandi and Malekzadeh, 1988; Weber and Camerer, 2003). In this paper, we first conjecture that banking groups engage in acquisitions and subsequently transfer their culture, including control systems and values related to risk, to newly acquired banking subsidiaries as part of their post-acquisition integration plans to homogenize practices within banking groups. We therefore formulate our main hypothesis:

Hypothesis 1: Acquiring banks transfer their corporate culture of risk assessment to their acquired subsidiaries.

Next, we develop two cross-sectional predictions following Angrist and Krueger (2001), who argue that most exogenous shocks have a heterogeneous effect across the treatment sample. That is, if our main hypothesis is true, the transmission of culture through acquisitions should vary in predictable ways across acquired banks.

There is a vast body of research in economics stressing the importance of geographic proximity for the diffusion of information. This notion has been particularly important in the urban economic literature that identifies "knowledge spillovers" as one of the three main reasons for the importance of agglomerations.[11] Information diffuses locally in part because physical proximity increases the ability of economic agents to exchange ideas and learn about important incipient knowledge, in particular tacit knowledge (e.g., Jaffe et al., 1993; Audretsch and Feldman, 1996; Matray, 2015). In the finance literature, geographic proximity has also been identified as crucial in the diffusion of information in the case of retail traders (Grinblatt and Keloharju, 2001; Coval and Moskowitz, 2001), analysts (Malloy, 2005), and institutional investors (Baik et al., 2010).

Prior studies also suggest that changes in agents' preferences and/or beliefs occur through repeated interactions (e.g., Guttman, 2003), which are facilitated by proximity. In the banking literature, a

[11] The other two reasons are the sharing of workers and the sharing of inputs. For surveys, the reader can refer to Audretsch and Feldman (2004), Moretti (2004), Feldman and Kogler (2010) and Carlino and Kerr (2014).

recent study by Gaspar (2015) relies on a plausibly causal setting and documents that a reduction in the distance between a bank's headquarters and its subsidiaries leads to improved monitoring. In the context of bank acquisitions, we then conjecture that the transfer of culture from groups to newly acquired subsidiaries is facilitated by the geographical proximity of the two organizations. Therefore, this leads to our second hypothesis:

Hypothesis 2: The transmission of corporate culture is stronger when acquiring and target banks are located in the same geographical area.

The prevailing view among practitioners is that corporate culture largely explains failures in M&A transactions. Specifically, insufficient compatibility between bidder and target firms' cultures is said to offset the expected synergies of the deal.[12] In line with this argument, Cai and Sevilir (2012) find that board connectedness plays an important positive role in M&A value creation. They suggest that such connections might help acquiring firms to assess *ex ante* the compatibility of firms' culture. M&A failures due to incompatible corporate cultures may also arise because of employees' post-merger actions. Indeed, prior studies provide evidence of post-merger resistance to acculturation (Weber and Camerer, 2003; Yu et al., 2005). As a result, studies also show, the ability of an acquirer to influence its target depends on its bargaining power (Capron and Shen, 2007). In the context of M&A, Masulis et al. (2007) argue that size serves as an effective takeover defense. That is, the larger the target firm relative to the acquiring firm, the more difficult it is for the acquiring firm to impose its values and processes. As a result, we posit that the transmission of corporate culture varies with the relative size of the target bank and formulate our third hypothesis:

Hypothesis 3: The transmission of corporate culture is stronger when the relative size of the target bank is smaller.

[12] See, for example, http://www.globoforce.com/gfblog/2012/6-big-mergers-that-were-killed-by-culture/

3.3 Data

In this section, we describe our sample selection, explain the procedure we followed to identify bank acquisitions, and present our data.

3.3.1 Data Sources

All banking institutions regulated by the Federal Deposit Insurance Corporation, the Federal Reserve, or the Office of the Comptroller of the Currency file Reports of Condition and Income, known as Call Reports. Call Reports include balance sheet and income data on a quarterly basis and also report the identity of the entity that holds at least 50% of a banking institution's equity stake (*RSSD9364*), which we use to link banking subsidiaries to their parent BHCs.

We restrict our sample period to the 1976 - 2005 period to avoid capturing the effect of the recent financial crisis. Our research design is built upon the use of Bank Holding Companies (BHCs, hereafter) subsidiaries' balance sheets data. One challenge in our setting is that ever since the enactment of the Riegle-Neal Act in 1995, BHCs have been allowed to consolidate their balance sheets nationwide. This implies that after 1995, only a subset of BHCs continued to report subsidiary level data.[13]

For each bank, we collect the amount of loan loss provisions (LLPs) (item *riad4230*) at the end of each fiscal year. In our sample, we scale LLPs by banks' total loans. We also obtain data on total assets (item *rcfd2170*), total loans (item *rcfd2122*), real estate loans (item *rcfd1410*), agricultural loans (item *rcfd1590*) and commercial and industrial loans (item *rcfd1600*), as well as loans to individuals (item *rcfd1975*) and non-performing loans (computed as the sum of items *rcfd1403* and *rcfd1407*). We remove observations for which the amount of loan loss provision is unavailable or negative. Finally, we retrieve information on each bank's state of location (item *rssd9210*) and its metropolitan statistical area (item *rssd9180*).

[13]To account for this empirical concern, we follow Landier et al. (2015) and perform a robustness test by restricting our sample up to 1995. We discuss this specification in Section 6 and find that our results remain unchanged.

We supplement our bank-level data with state-level data. Specifically, we obtain data on state population and state population income from the Regional Tables of the Bureau of Economic Analysis.

3.3.2 Acquisition-Level Variables

Our identification strategy relies on identifying banks that are acquired by another BHC on a given date. To do so, we use the fact that all banks report their own BHC in the call reports database (item *rssd9348*). To identify acquisitions, we then simply look for changes in the reported BHC.[14] Figure 1 plots the distribution of bank acquisitions over our sample period. We only use the acquisitions between 1978 and 2003 in order to have at least two years of data pre and post acquisition for all acquired banks in our sample. On average, there are 226 acquisitions per year. The minimum number of acquisitions, 64, was achieved in 2003. The maximum number of acquisitions, 411, occurred in 1986. Graphically, we observe that banks' acquisitions were more intense during the 1980*s*. This phenomenon occurred as a response to the staggered adoption of state laws that allowed banks to expand their activities both within state and across states (e.g., Jayaratne and Strahan, 1996).

For each acquisition, we identify all subsidiaries that were owned by the acquiring BHC in the quarter preceding the acquisition. We then use this group of banks to compare the LLP comovement with the newly acquired bank before and after the acquisition date. To do so, we compute the end of fiscal year mean of loan loss provisions of this group in the period composed of the eight years before the acquisition year and the eight years following the acquisition year. A subsidiary of this banking group remains in the group as long as the ultimate BHC does not change.

Our final dataset is a panel of $1,854$ acquisitions of public and private banks where, for each acquisition, we obtain the end of year LLP of the acquired bank, denoted i and the average LLP of the other subsidiaries of its acquiring BHC, denoted j.[15] We also follow Landier et al. (2015) and

[14] A bank that does not have a BHC is classified as an independent bank following Landier et al. (2015).

[15] To account for changes in the composition of the banking group, we focus only on the set of subsidiaries that were owned by the BHC before the acquisition when we compute the average LLP.

identify the location of the acquiring BHC as the state in which it has its largest share of assets the quarter preceding the acquisition.

3.3.3 Loan Loss Provision as a Proxy for Risk Culture

Throughout our analyses, we use loan loss provisions as a discretionary measure in the context of risk assessment. The use of LLPs raises two concerns. First, to what extent are LLPs discretionary? Second, do LLPs represent an item that is economically significant?

First, loan loss provisions represent an accrued expense that a bank sets aside to cover potential losses on loans. Under U.S. GAAP, the accounting model for recognizing credit losses is commonly referred to as an "incurred loss model". Indeed, accounting guidance requires only that banks estimate their provision using all observable data on probable losses that have not occurred yet. Thus, critics often argue that such estimates are highly subjective. To further gauge the subjectivity and variation inherent in banks' loan loss provisioning, we follow Beatty and Liao (2011) and regress the level of LLPs on changes in non-performing loans in year t and year $t-1$.[16] Figure 2 plots the difference between the observed and predicted levels of LLPs. Graphically, we observe substantial variation across banks in our sample. This heterogeneity is consistent with bank managers having significant discretion in estimating LLPs, which leads to variation in the level of conservatism embedded in their risk assessment practices.

Second, loan loss provisions constitute the largest accrual in banks' financial statements. Consequently, the role of LLPs in the recent financial crisis has attracted attention from regulators and standard setters. Indeed, a recent study by Ng and Roychowdhury (2015) documents that loan loss provisions, which are added back into banks' Tier 2 capital ratio, are positively associated with bank failure risk. Other studies find that characteristics of loan loss provisions are associated with the risk-taking profile of banks (e.g., Bushman and Williams, 2012, 2015). As a result, there is currently a global debate about whether to shift from an incurred loss model to an expected loss

[16] We also add earnings before loan loss provision in our model. However, we do not include the Tier 1 risk-adjusted capital ratio, since this information is not available for private banks throughout our sample period.

model to estimate loan loss provisions in a more timely manner, which should enhance the stability of the financial system.

3.3.4 Summary Statistics

Our sample differs significantly from that used in the majority of previous accounting studies since we study the entire universe of U.S. banks, while most studies examine the behavior of publicly listed U.S. banks.[17] Indeed, our objective is to maximize the size of our sample to draw causal inferences and exploit variation in the characteristics of bank acquisitions to strengthen our claim. As a result, our main sample contains 56,145 bank-year observations for 4,585 U.S. banks that are acquired during our sample period. Target banks are located in the same metropolitan statistical area (MSA, hereafter) in 11% of the transactions.

Table 1 displays the summary statistics for our sample of 1,854 acquisitions over the 1976 to 2005 period. This table reveals that, on average, acquiring banking groups are composed of approximately 10 subsidiaries in the quarter preceding the acquisition and make 15 acquisitions on average during our sample period. Target banks belongs to banking groups that are, on average, composed of almost 4 subsidiaries. However, the distribution is skewed since at the median, target banks are independent.

Table 2 displays the bank-level summary statistics for our main sample of 56,345 bank-year observations over the 1976 to 2005 period. Target banks' loan loss provisions represent, on average, 0.67% of banks' total loans. For our acquiring banking groups, the average LLPs represent 0.61% of banks' total loans. At the mean (median) of the distribution, banking groups' size (proxied by total assets) is \$6.9 (\$1.0) billion. For target banks, the average size is \$379 million, while the median is \$57 million. Given the skewed distribution of bank size, we take the logarithm of total assets in our regression analyses. These figures are generally similar to those in Jiang et al. (2015), who examine the behavior of BHC as a response to banking deregulation. However, in our sample the standard deviation and absolute values of our growth variables, are larger (more volatile)

[17] See Beatty and Liao (2014) for a recent review of the accounting literature on banks.

presumably because our sample is composed of target banks that are, on average, more than ten times smaller than their BHCs.

3.4 Identification Strategy

Our main hypothesis is that corporate culture is transmitted from acquiring banks to acquired banks after the completion of the transaction. We test this conjecture empirically by comparing the change in the comovement of the LLPs between newly acquired banks and subsidiaries already owned by the acquiring BHC before and after the acquisition date. This approach treats acquisitions as cultural shocks and builds on the work of Barberis et al. (2005) and Boissel (2014). The central intuition is that this comovement should increase after the acquisition date, since target banks start being influenced by the corporate culture of acquiring banking groups. Specifically, we estimate the following difference-in-differences model:

$$
\begin{aligned}
LLP_{i,t} = Post\ Acquisition_{i,t}\ +\ LLP\ BHC_{j,t}\ +\ LLP\ BHC_{j,t}\ \times\ Post\ Acquisition_{i,t} \\
+\ Bank\ Controls_{i,t} + State\ Controls_{s,t} \\
+\ Controls_{i,j}\ \times\ Post\ Acquisition_{i,t} + \gamma_t + \epsilon
\end{aligned}
\quad (3.1)
$$

In this model, i indexes acquired banks, j indexes acquiring BHC, s indexes state and t indexes time. The dependent variable, $LLP_{i,t}$, is the end of year loan loss provision of the acquired bank i in year t. *Post Acquisition* is an indicator variable that equals one after the acquisition of bank i by the acquiring BHC j, and zero otherwise. $LLP\ BHC_{j,t}$ is the end of year average loan loss provisions of all subsidiaries already owned by the acquiring banking group j in the quarter preceding the acquisition.[18] In this model, $\theta_{i,j}$ represents acquisition fixed effects and γ_t represents year fixed effects. Acquisition fixed effects capture time-invariant characteristics of the acquisition such as

[18] We use simple averages of all subsidiaries' loan loss provisions for our main set of tests. However, in Section 6, we provide evidence that our results are robust to using weighted averages that take into account the relative size of subsidiaries within the banking group.

bank-specific shocks that could drive the decision to acquire a bank and future comovements in LLP.[19] Year fixed effects control for aggregate shocks and common trends in M&A activity and LLP decisions. Finally, in the most stringent specifications, we follow Bertrand and Mullainathan (2003) and Gormley and Matsa (2014) and augment our model with State × Year fixed effects. This removes any time varying shocks and state characteristics that might affect banks' acquisitions and LLP decisions, including state business cycles and time-varying state institutional differences (e.g., banking regulation, marginal tax rate).

The variable of interest is *LLP BHC × Post Acquisition*. Its coefficient corresponds to our difference-in-differences estimate that measures whether the LLP of a target bank comoves more or less with that of an acquiring BHC *following* the acquisition. The identification relies on comparing the comovement of LLP before and after the acquisition relative to a control group of banks that have not been acquired yet. Again, our hypothesis predicts that this coefficient should be positive and statistically significant to reflect a transfer of corporate culture in risk practices between acquiring banking groups and target banks.[20] It is important to note that in all our specifications, when controls are introduced, we also add the controls interacted with the dummy *Post Acquisition Controls × Post Acquisition*. This authorizes the effect of control variables to vary non parametrically after the acquisition. In particular, it allows us to take into account the possibility for underlying risks of loans to vary after the acquisition, and makes sure that the change in LLP choice we observe is *not* driven by a change in the loan portfolio.

Our variation in corporate culture comes from banking acquisitions. Thus, we cluster standard errors by acquisition.[21] This clustering method accounts for potential time-varying correlations in omitted variables that affect both acquiring and target banks around the acquisition (Bertrand et al., 2004). We further add two sets of control variables to our model. First, we include various bank level controls that are known to be prime determinants of loan loss provisions and could

[19] Acquisition fixed effects are defined for each acquisition event, i.e., each pair of a newly acquired bank and an acquiring BHC.

[20] In section 6, we implement another strategy to account for the possibility that acquired banks differ significantly from non-acquired ones. Specifically, we use a matching algorithm to create a control group of placebo banks that are not acquired but share similar characteristics with acquired banks.

[21] We find similar results if we cluster the standard errors at the BHC or state level.

plausibly affect acquisition decisions as well. We follow the models described in Beatty and Liao (2014) and incorporate banks' leverage, size, loan growth, non-performing loan growth and loan concentration to our model. Second, we also include state-level controls to reduce the risk that our results are driven by changes in local economic conditions rather than the acquisition itself and the induced change in corporate culture. This list of controls includes state population, personal income, and personal income growth.

3.5 Results

3.5.1 Baseline Results

We start by providing a graphical illustration of the increase in LLPs' comovement around the bank acquisition date. To do so, we first compute correlation between the LLPs of the target bank and the acquiring banking group. We do this on a yearly basis using a five-year centered moving window starting six years before the acquisition and ending six years after.[22] We then calculate the average correlation on a given year relative to the acquisition year, and we plot it in Figure 3. Graphically, the correlation is flat before the acquisition and rises sharply right after the acquisition. Note that if it starts to increase two years before the acquisition date, this is simply because we use a five year centered window to compute correlations. This clearly indicates that the LLP comovement of a target and the subsidiaries of the acquiring BHC is strongly affected after the acquisition, in line with our predictions. The correlation increases approximatively threefold after the acquisition, from 0.1 to 0.27, an economically highly significant effect.

We next turn to our multivariate analyses and test our main hypothesis by formally estimating the empirical model described in Equation (1). Table 3 displays the results. The coefficient on *LLP BHC* × *Post Acquisition* is positive and statistically significant at the 1% level across all specifications, suggesting that the comovement in LLPs between target and acquiring banks increases significantly after the acquisition. In column (1), we report the estimation of our model

[22] For example, in the year of the acquisition, we compute the correlation using the target's and the BHC LLPs in years -2, -1, 0, +1 and +2, where year 0 refers to the acquisition year.

with acquisition fixed effects only. In column (2), our results hold when we add year fixed effects that control for macroeconomic shocks. In column (3), we replace year fixed effects by state × year fixed effects to account for time-varying unobservable events at the state level, including changes in state regulation. Specifically, including state × year fixed effects rules out the concern that our effects could be driven by heterogeneity in banking deregulation across U.S. states. Finally, in column (4), we augment our model with bank and state-level covariates and interact each control with our *Post Acquisition* dummy, to capture in a flexible way all variations after the acquisition. Our results indicate that target banks' LLPs after the acquisition takes place, follow a pattern that is more similar to that of their acquiring BHC, after we account for macro-economic shock and observable economic determinants of loan loss provisions. Note that the coefficient on *LLP BHC* is positive and statistically significant too. This indicates that there is a pre-acquisition comovement between target and acquiring banks. However, the magnitude of the effect is sharply reduced in column (3) when we introduce state × year fixed effects, while the magnitude of the coefficient on *LLP BHC* × *Post Acquisition* remains unchanged. This suggests that the pre-acquisition comovement is largely explained by local shocks while the post-acquisition increase in comovement is likely driven by transmission of risk assessment practices within banking groups.

Recall that in our main analysis, we examine the comovement in raw levels of loan loss provisions between acquired and acquiring banks and do not use discretionary/abnormal levels in LLPs. Thus, we need to control for risk factors that affect LLP decisions to ensure that our results are not simply driven by a convergence in economic signals regarding future loan defaults. The control variables reported in Table 3 carry the expected sign discussed in Beatty and Liao (2014). For example, changes in non-performing loans are positively related to contemporaneous levels of loan loss provisions.[23] The coefficient on *Log(Asset)* is not statistically significant, whereas it is positive and statistically significant in other studies. This is due to the inclusion of acquisition fixed effects in our model, while the target bank's size is unlikely to vary significantly around the acquisition date. The coefficient on *Loan growth* is negative and statistically significant as in the different models

[23]Indeed, for our sample of U.S. banks, the standards for LLPs are derived from an incurred loss model. That is, banks have to rely on observed factors that change the probability that loans will default. Thus, if loans are not independent from each other in a bank's balance sheet, an increase in non-performing / defaulting loans likely predicts an increase in future defaults.

reported in the Beatty and Liao (2014) survey paper. Furthermore, the coefficient on *Personal income growth* is negative and statistically significant, consistent with the idea that increases in local household income reduce the risk of future default on existing loans.

To gauge the magnitude of the effect, consider our most demanding specification from Column (3) which includes state $\times$ year fixed effects. Our estimation shows that a one standard deviation increase in the acquiring BHC's LLP leads to a rise of 0.09 $(0.15 * 0.64)$ for that of the target bank, which corresponds to 15% of the target bank's average LLP. Our effect is therefore economically significant and in line with Figure 3 in which we document that the correlation between target banks' and acquiring BHCs' LLPs increases threefold, on average, after the acquisition date.

One legitimate concern is that acquiring banks might select their target banks because they have similar risk assessment practices. To rule out this endogeneity concern, we further decompose our *Post* variable in year dummies around the acquisition date. We present graphical evidence in Figure 4. We observe that the comovement in LLPs between acquiring banking groups and target bansk does not increase before the acquisition date. This indicates that acquiring groups do not select banks with increasingly similar risk practices before the transaction. Furthermore, the figure suggests that the increase in comovement is not statistically different from zero until two years after the acquisition. This is consistent with the idea in organization theory that it takes time to transmit corporate culture across organizations. Next, we find that the effect is permanent. This rules out an additional concern that acquiring banks might selectively acquire new banking subsidiaries to benefit from short-term discretionary risk assessments.[24]

We further corroborate our results with multivariate tests. Table 4 reports the results of our estimation of Equation (1) with a decomposition of our effect.[25] The coefficients on the years $t-5$ to $t-1$ interacted with the loan loss provision of the BHC are not statistically different from zero across the four specifications. This again indicates that the increase in comovement in LLPs between target banks and acquiring banking groups was not anticipated. The coefficient on years t and $t+1$ are not statistically different from zero either, which suggests that the transmission of

[24] The benefits include earnings management and circumventing capital adequacy requirements.

[25] In Table 4, we do not report the non-interacted coefficients on *Post Acquisition* and *LLP BHC* for ease of presentation.

corporate culture takes two years to be effective. The coefficient of interest is then positive and statistically significant for years $t+2$ to $t+5$. Its magnitude is increasing over time, suggesting that the corporate culture of the BHC slowly influences the risk assessment practices of the newly acquired subsidiary. Finally, the results in Table 4 confirm that the increase in LLP comovement is permanent, since the coefficient on years $t+6$ and onward is positive and statistically significant.

3.5.2 Cross-Sectional Results

In the previous subsection, we present empirical evidence consistent with our first hypothesis that corporate culture in the context of risk assessment is gradually transmitted from acquiring groups to acquired banks. In this subsection, we further explore whether the transmission of corporate culture is more pronounced for some specific sub-samples of banks, and we formally test our second and third hypotheses.

First we test our second hypothesis that the transmission of corporate culture is more pronounced when acquiring banking groups and target banks are located in the same geographical area. To do so, we create an indicator variable, *Same MSA*, that equals one if acquiring BHCs and target banks are located in the same metropolitan statistical area, and zero otherwise. This happens in 11.6% of the acquisitions in our sample. Table 5 reports the results. The coefficient on *LLP BHC* $\times$ *Post Acquisition* is positive and statistically significant at the 1% level across all specifications. This suggests that after the acquisition, target banks' LLPs follow a pattern that is closer to that of their acquiring BHC when target banks are located in a different MSA compared to their acquiring BHC. Furthermore, the coefficient on *LLP BHC* $\times$ *Post Acquisition* $\times$ *Same MSA* is also positive and statistically significant at the 1% level in the four specifications. This indicates that the increase in the comovement in LLPs between acquiring banking groups and target banks is two times stronger when both banks are located in the same MSA than when banks are not located in the same MSA. This supports our second hypothesis that geographical proximity enhances the transmission of corporate culture in acquisitions.

Next, we test our third hypothesis that the transmission of corporate culture is stronger when the relative size of target banks is smaller. To do so, we first compute a continuous variable, $(Size\ Acquired)/(Size\ BHC)$, equal to the ratio of the target bank size over the size of the acquiring BHC. Larger values indicate that the size of the target bank is higher relative to that of its acquiring BHC. Table 6 displays our results. The coefficient on $LLP\ BHC \times Post\ Acquisition$ is positive and statistically significant at the 1% level, while the coefficient on $LLP\ BHC \times Post\ Acquisition \times (Size\ Acquired)/(Size\ BHC)$ is negative and statistically significant at the 1% level across all specifications. This suggests that the increase in comovement between acquiring and target banks' LLP is, on average, smaller when the relative size of the target is high. Specifically, our analysis reveals that moving from the 25^{th} to the 75^{th} percentile in terms of size ratio decreases the comovoment in LLPs by 25%. The results in Table 6 are in line with our third hypothesis that the larger the target bank is relative to the acquiring BHC, the more resistant it is to the transmission of corporate culture in acquisitions.

The last cross-sectional prediction

3.6 Robustness Tests

In this section, we perform various additional tests to ensure the robustness of our main findings and the validity of our research design to support a causal claim.

Sample period Our dataset is a panel of banks from 1976 to 2005. As noted in Section 3.1, one challenge is that following the enactment of the Riegle-Neal Act in 1995, BHCs were allowed to consolidate their balance sheets nationwide. This implies that after 1995, only a subset of BHCs continued to report subsidiary-level data. To account for this concern, we follow Landier et al. (2015) and perform a robustness test in which we restrict our sample to the 1976 - 1995 period. Table 7 displays the results. The coefficient on $LLP\ BHC \times Post\ Acquisition$ remains positive and statistically significant at the 1% level across all four specifications. This indicates that our results are not affected by variations in our sample period.

Matching Strategy One additional concern is that acquired banks may systematically differ from non-acquired ones. In Section 5, the results in Figure 4 and Table 4 already indicate that banking groups do not select target banks based on similar patterns in loan loss provisions prior to the acquisition. That is, acquiring and target banks do not share increasingly similar risk assessment cultures before the acquisition. However, one endogeneity concern remains, since we cannot fully rule out the existence of a common factor between target banks and yet-to-be-acquired target banks (our control group throughout the previous section) that would lead to an increase in the comovement in LLPs between acquired and acquiring groups that is not related to the acquisition itself.

To account for this endogeneity concern, we use a matching strategy to create an additional control group of non-acquired banks. Specifically, for each acquired bank we select its nearest neighbor from the set of banks that are located in the same U.S. state and are not acquired during our sample period. We match banks on all the controls use previously.[26] We require our matched banks to be relatively comparable to their acquired counterparts, which leads to a decrease of a third in the number of unique acquisitions used to create this additional control group.[27] Appendix B presents the descriptive statistics for our sample of acquired and matched banks. The univariate tests suggest that the two groups are comparable, even if we acknowledge that acquired banks present a slightly higher ratio of equity over total assets.

We next examine whether the comovement in LLPs also increases between matched banks and acquiring banking groups. We create an indicator variable, *Treated*, that equals one for acquired banks, and zero otherwise. Table 8 reports the results. The coefficient on *LLP BHC* $\times$ *Post Acquisition* is not statistically different from zero in the four specifications. This indicates that we fail to find an increase in the comovement in LLPs between acquiring groups and the closest local neighbors to acquired banks. On the contrary, the coefficient on *LLP BHC* $\times$

[26] We follow Frésard and Valta (2015) and use a matching algorithm that reduces the Mahalanobis distance across treated and matched banks. Our results are qualitatively similar if we use a propensity score matching technique.

[27] Specifically, we drop matched and acquired banks for which the Mahalanobis distance between matched and acquired banks is higher than 0.7. This criterion ensures that acquired and matched firms are statistically comparable in the year preceding the acquisition. However, in untabulated tests we find that our results are robust to the inclusion of matched banks that are not fully statistically comparable before the acquisition.

Post Acquisition × *Treated* is positive and statistically significant in all specifications. In short, we find that the comovement in LLPs increases only for acquired banks and not for their matched counterparts. We interpret this result as evidence that we capture the causal effect of the transmission of corporate culture from acquiring to target banks rather than a spurious effect due to acquired banks' characteristics.

Regulation and Technology One concern is that our results could be driven by changes in banking regulation. Indeed, a recent study by Jiang et al. (2015) provides evidence that increased competition due to state-level banking deregulation leads to a decrease in discretionary accruals for BHCs. We first rule out this concern by adding state × year fixed effects in our model, that controls for time-varying changes in deregulation at the state level. However, to further investigate this possibility, we perform an additional test and cut our sample into two periods. Specifically, we split our sample based on whether acquisitions where performed before or after 1990. The intuition for this test is that since the first set of significant interstate deregulation events occurred in the late 1970*s* and in the 1980*s*, our effect should be concentrated in the pre-1990 period if we are capturing primarily a change in behavior driven by banking deregulation. However, as reported in Table 9, the coefficients on *LLP BHC* × *Post Acquisition* are statistically significant at conventional levels for both the pre-1990 period (columns (1) and (2)) and the post-1990 period (columns (3) and (4)).[28]

Discretionary loan loss provision In our analyses, we examine the change in comovement in loan loss provision for acquiring and target banks around the acquisition date using raw levels of LLPs. An alternative methodological choice is to follow a two-stage process. Indeed, other accounting studies usually first predict the level of LLP using observable characteristics and then use the residuals of this regression as the discretionary / unexplained level of LLP in their tests (see Section 5 in Beatty and Liao (2014) for a review of such models). In Table 10, we repeat our main analysis except that we replace target and acquiring banks' LLPs in our model with the unexplained

[28]The coefficient in column 4 of Table 9 is statistically significant only at the 10% level, which is plausibly due to a statistical power issue of our sample since the number of acquisitions is smaller post 1990 than pre 1990, as depicted in Figure 1.

part of LLPs used to plot Figure 2.[29] Our results remain unaffected. Note that the two approaches are very similar, since in our main tests we explicitly control for the determinants used to predict normal / expected level of LLPs. This means that in our previous tests, we document an increase in the comovement in LLPs that is not explained by observable bank and state characteristics. In other words, we capture the effect of corporate culture on bank managers' discretion in assessing provisions for future loan losses.

Measure of loan loss provision In our analyses, we use as a covariate the average LLP of acquiring banking groups computed as the simple average of LLP for all subsidiaries of this banking group already owned by the BHC in the year before the acquisition. As a robustness test, we compute this variable as the weighted average of LLP of all subsidiaries already owned by the BHC prior to the acquisition, using subsidiary size (total assets) as a weighting criterion. Table 11 displays the results. The coefficient on $Post\ Acquisition \times LLP\ BHC$ is positive and statistically significant at the 1% level across all specifications, indicating that our results are not affected by our methodological choice in computing the BHC average loan loss provision.[30]

3.7 Conclusion

In this paper, we attempt to shed light on how corporate culture, defined as both formal control systems and informal values, is transmitted across organizations. To do so, we use bank acquisitions and provide causal evidence of a transmission of corporate culture in terms of risk assessment from acquiring groups to acquired banking subsidiaries. Specifically, we find an increase in comovement in target and acquiring banks' loan loss provisions after the acquisition. We perform multiple robustness tests and ensure that our results are unlikely to be explained by reverse causality and

[29]Specifically, we follow Beatty and Liao (2011) and regress the level of LLPs on changes in non-performing loans in year t and year $t-1$.We also add earnings before loan loss provision in our model. However, we do not include the Tier I risk-adjusted capital ratio in our model, since this information is not available for private banks throughout our sample period.

[30]Note that we do not take the raw level of the BHC's LLP directly, since we want to compare the change of comovement in LLP between the already owned subsidiaries and the newly acquired one.

selection concerns. Our results are relevant to regulators who attempt to circumvent risky behavior in the financial industry that could jeopardize the stability of financial markets.

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Figure 3.1: **Distribution of Bank Acquisitions over Time**

The figure shows the number of acquisitions for each year in our sample. The acquisitions are determined by changes in ultimate ownership using the Bank Holding Company item of the FED Call Reports database. In our main analysis, the sample period is 1976 to 2005. We thus restrict our sample of acquisitions to the 1978 to 2003 period to ensure that we have at least two years of data pre and post acquisition for all target banks in our sample.

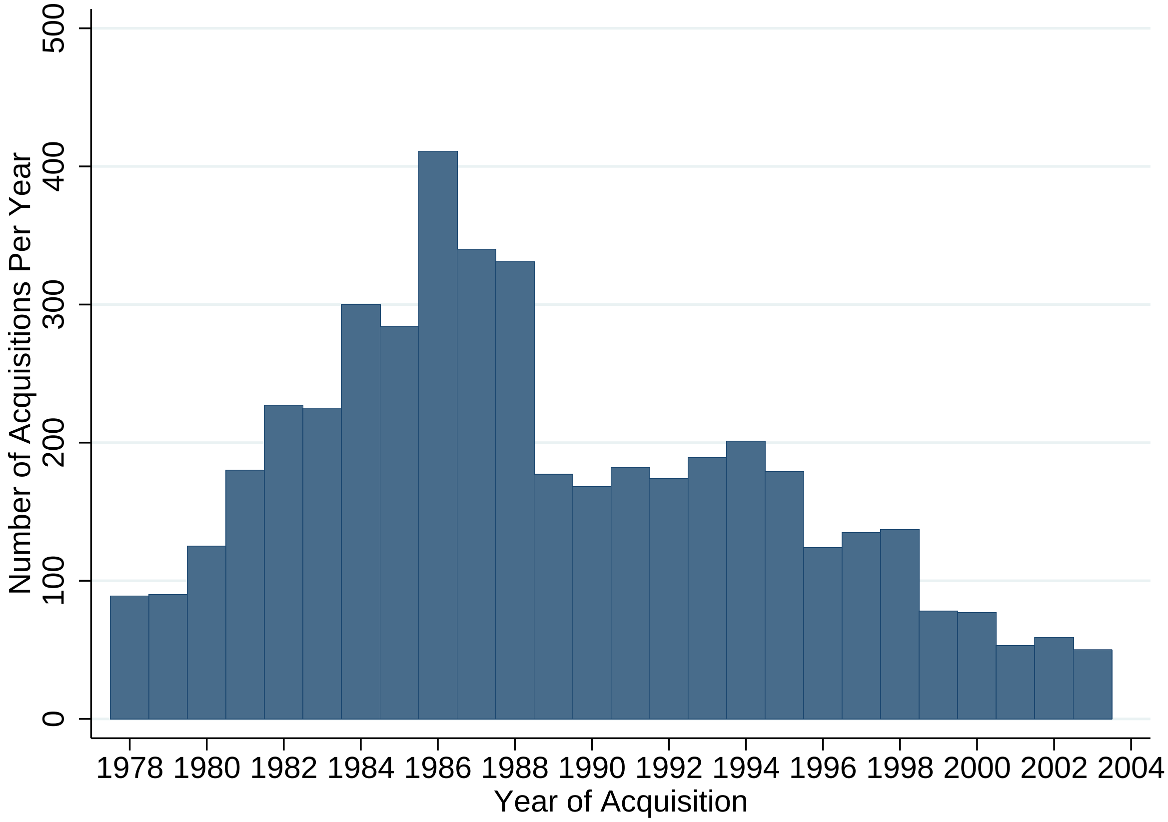

Figure 3.2: **Distribution of Loan Loss Provision Residuals**

This graph plots the distribution of loan loss provision residuals for our sample of bank-year observations. We follow Beatty and Liao (2011) and regress the level of LLPs on changes in non-performing loans in year t and year $t-1$.We also add earnings before loan loss provision in our model. However, we do not include the Tier I risk-adjusted capital ratio in our model, since this information is not available for private banks throughout our sample period.

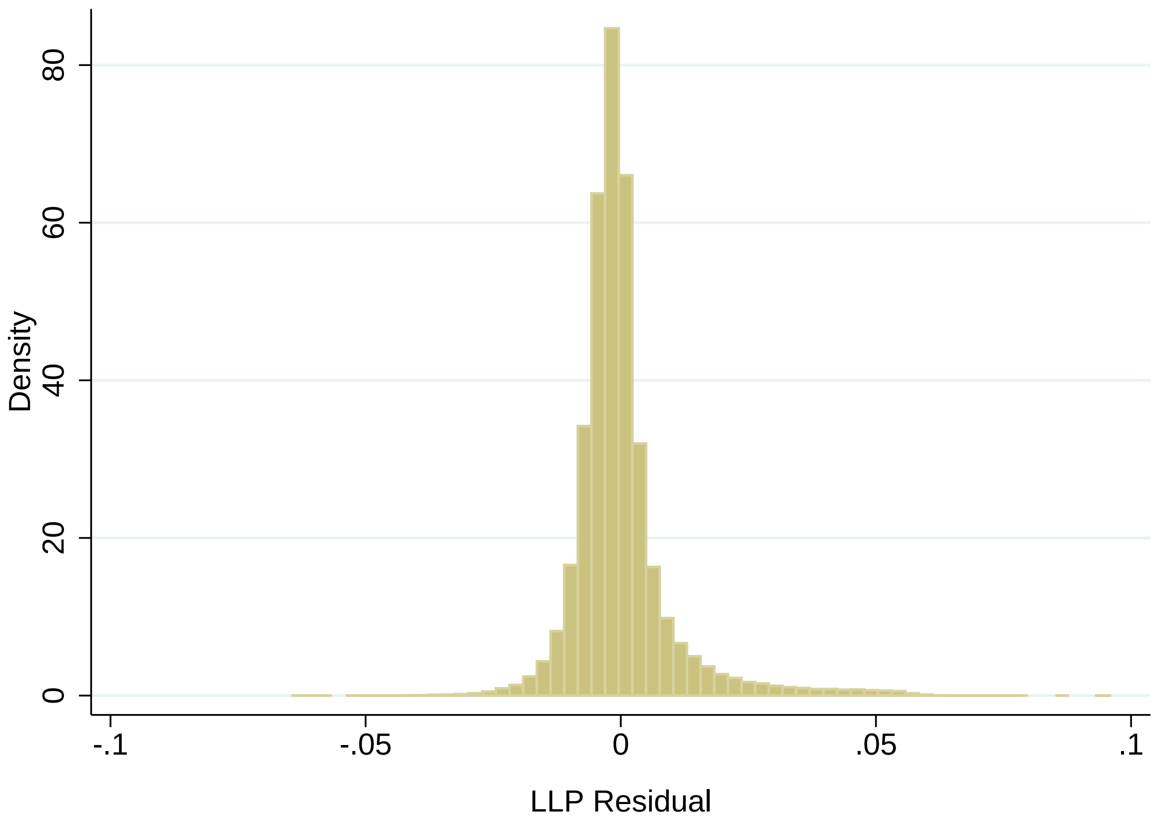

FIGURE 3.3: **LLP Correlation around Bank Acquisition**

The figure shows the evolution of the average correlation in LLPs between the target and other subsidiaries of the acquiring banking group around the year of acquisition. The correlation is computed using a five-year centered window, and we then take the average across all acquisitions. This figure plots the average correlation for the period starting six years before the acquisition and ending six years after the acquisition.

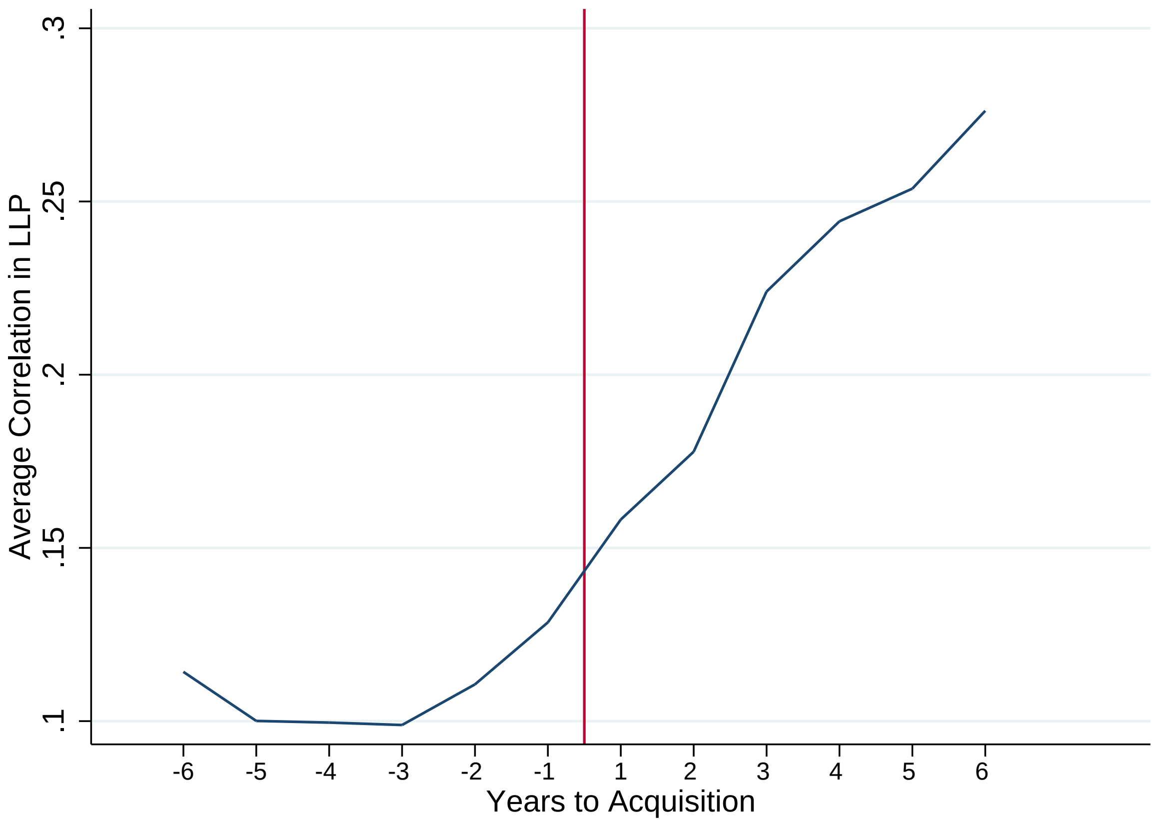

Figure 3.4: **Loan Loss Provisions Comovement around Acquisition**

This figure shows the evolution of comovement in LLP between acquiring banks and target banks around the acquisition date. The specification is the same as in Equation (1) except that the *Post Acquisition* variable is replaced by a collection of variables, *Acquisition*(k), where *Acquisition*(k) is a dummy equal to one exactly k years after (or before if k is negative) the BHC acquires the target bank. The solid line plots the point estimates for $k = -6, \ldots, 6$, using the acquisition years $k < 6$ as the reference years. The dashed lines plot the 95% confidence interval.

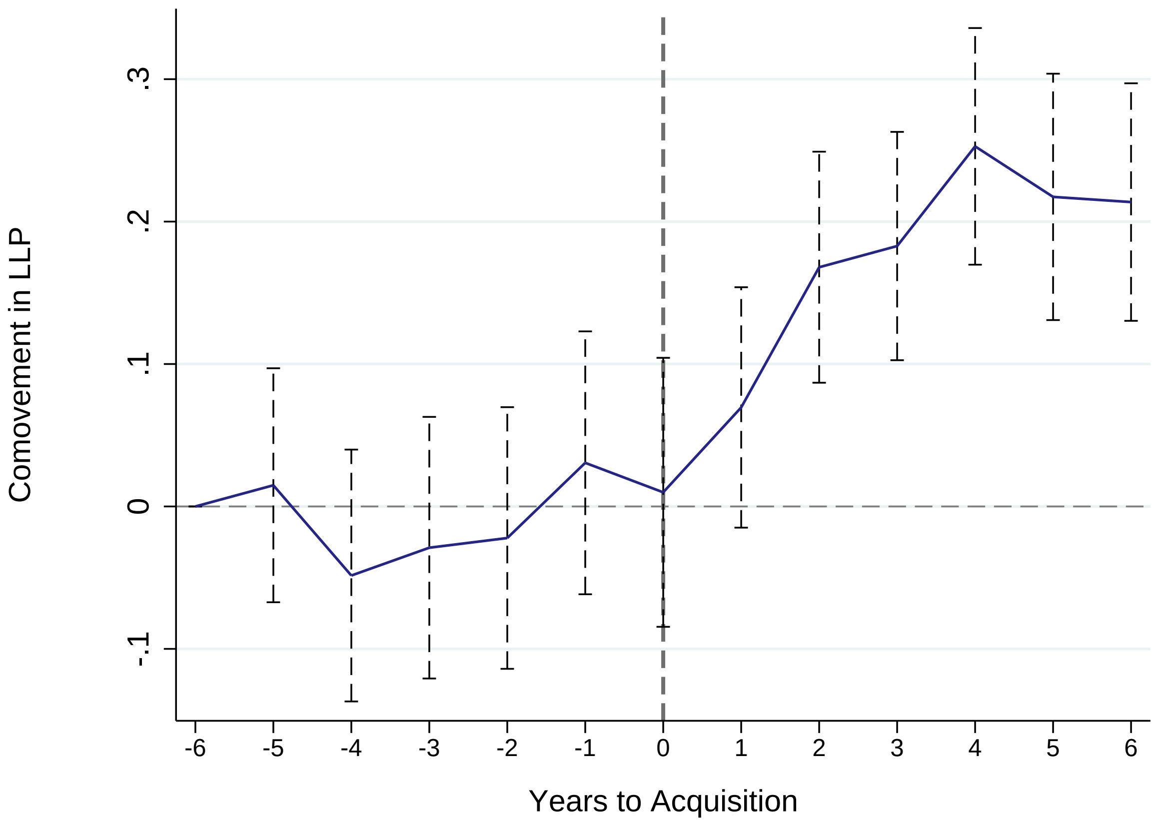

Table 1: Summary Statistics - Acquisitions

This table presents the descriptive statistics for our sample of banking acquisitions over the 1976 to 2005 period.

	Mean	25^{th}	Median	75^{th}	Std Dev.
Target Bank Total Loans (Millions)	192.649	13.225	28.633	64.652	1,637.561
Acquiring Bank Total Loans (Millions)	4,171.310	93.194	569.014	2,738.154	13758.202
Number Subsidiaries per Acquiring Bank	10.358	1.000	4.000	13.000	13.485
Number Subsidiaries per Target Bank	3.791	1.000	1.000	2.000	7.808
Number of Mergers Per Acquiring Bank	15.414	2.000	8.000	19.000	20.387
BHC Target Total Assets/Acquiring Bank Total Assets (%)	33.790	4.8001	14.760	41.012	47.567
Dummy Same MSA Target/Acquiring Bank	0.116	0.000	0.000	0.000	0.321
Observations	4,585				

Table 2: Summary Statistics - Bank Panel

This table presents the descriptive statistics for our panel of bank-year observations over the 1976 to 2005 period.

	Mean	25^{th}	Median	75^{th}	Std Dev.
Target LLP/Total Loans (%)	0.672	0.164	0.383	0.795	0.823
Target Total Assets (Millions)	379.560	27.600	57.026	126.901	4,084.158
Target Total Loans (Millions)	66.004	14.076	30.496	72.065	86.005
Target Loan Growth (%)	11.403	0.007	8.137	17.898	21.217
Target Non-Performing Loans Growth (%)	68.371	-48.375	-10.600	58.762	281.746
Target Leverage (%)	8.486	6.836	7.919	9.437	2.729
Target Loan Concentration	0.403	0.340	0.389	0.464	0.136
Acquiring Bank Subsidiaries Average LLP/Total Loans (%)	0.618	0.242	0.445	0.771	0.648
Acquiring Bank Total Loans (Millions)	4,220.148	91.819	624.612	3,007.472	12833.856
Acquiring Bank Total Assets (Millions)	6,894.254	162.968	1,063.680	5,233.011	20223.965
State Population (Millions, Log)	15.521	15.010	15.461	16.250	0.824
State Personal Income (Millions, Log)	18.137	17.540	18.146	18.818	0.925
State Personal Income Growth	6.883	4.897	6.321	8.532	2.958
Observations	56,345				

Table 3: Baseline Results

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, corresponds to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.3273***	0.1940***	0.0612***	0.1776***
	(0.0147)	(0.0147)	(0.0145)	(0.0148)
Post Acquisition	-0.0021***	-0.0019***	-0.0016***	-0.0064***
	(0.0001)	(0.0002)	(0.0002)	(0.0023)
LLP BHC × Post Acquisition	0.1685***	0.1735***	0.1504***	0.1142***
	(0.0184)	(0.0181)	(0.0188)	(0.0190)
Leverage				-0.0625***
				(0.0043)
Log(Asset)				0.0001
				(0.0002)
Loan Growth				-0.0083***
				(0.0004)
Loan Concentration				-0.0001
				(0.0009)
Non-Performing Loans Growth				0.0001***
				(0.0000)
Non-Performing Loans Growth (t-1)				0.0002***
				(0.0000)
Population				-0.0115***
				(0.0031)
Personal Income				0.0073***
				(0.0023)
Personal Income Growth				-0.0274***
				(0.0031)
Observations	56,145	56,145	56,145	53,425
R-Square	0.34	0.41	0.40	0.37
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-

Table 4: Baseline Results - Decomposition

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, correspond to the loan loss provision of target banks. We break the *Post Acquisition* dummy with paired yearly dummies around the acquisition date. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. The non-interacted *LLP BHC* and *Post Acquisition* variables are not reported for ease of presentation. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC × Post Acquisition (t-5,t-3)	-0.0607	-0.0328	-0.0190	-0.0315
	(0.0522)	(0.0474)	(0.0301)	(0.0324)
LLP BHC × Post Acquisition (t-2,t-1)	-0.0467	-0.0292	-0.0137	-0.0462
	(0.0470)	(0.0430)	(0.0291)	(0.0284)
LLP BHC × Post Acquisition (t,t+1)	0.0137	0.0229	0.0336	0.0083
	(0.0529)	(0.0535)	(0.0377)	(0.0400)
LLP BHC × Post Acquisition (t+2,t+3)	0.1185**	0.1430***	0.1489***	0.1206***
	(0.0555)	(0.0493)	(0.0359)	(0.0302)
LLP BHC × Post Acquisition (t+4,t+5)	0.2129***	0.2361***	0.2060***	0.1776***
	(0.0558)	(0.0437)	(0.0292)	(0.0267)
LLP BHC × Post Acquisition (≥t+6)	0.2235***	0.2424***	0.2128***	0.2067***
	(0.0588)	(0.0415)	(0.0336)	(0.0334)
Observations	56,024	56,024	56,024	53,425
R-Square	0.34	0.41	0.40	0.37
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
Bank Controls	-	-	-	Yes
State Controls	-	-	-	Yes

Table 5: Cross-Sectional Results - Geographic Proximity

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, corresponds to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. *Same MSA* is an indicator variable equal to one if the acquiring banking group and its target bank are located in the same metropolitan statistical area. The single term is absorbed by the Acquistion FE. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.3458***	0.2099***	0.0720***	0.1936***
	(0.0154)	(0.0154)	(0.0151)	(0.0156)
LLP BHC × Same MSA	-0.1835***	-0.1522***	-0.0978**	-0.1316***
	(0.0461)	(0.0446)	(0.0440)	(0.0444)
Post Acquisition	-0.0021***	-0.0019***	-0.0016***	-0.0058**
	(0.0001)	(0.0002)	(0.0002)	(0.0024)
Post Acquisition × Same MSA	-0.0002	-0.0007*	-0.0006	-0.0034
	(0.0004)	(0.0003)	(0.0003)	(0.0073)
LLP BHC × Post Acquisition	0.1519***	0.1567***	0.1365***	0.1034***
	(0.0197)	(0.0194)	(0.0202)	(0.0204)
LLP BHC × Post Acquisition × Same MSA	0.1696***	0.1633***	0.1283***	0.1250**
	(0.0528)	(0.0503)	(0.0479)	(0.0515)
Observations	56,024	56,024	56,024	53,425
R-Square	0.35	0.42	0.43	0.40
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
Bank Controls	-	-	-	Yes
State Controls	-	-	-	Yes

Table 6: Size Ratio Cross Section

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, corresponds to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. *(Size Acquired) / (Size BHC)* is a continuous variable equal to the ratio of the target bank's size over the acquiring banking group's size. The single term is absorbed by the Acquistion FE. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.3201***	0.1778***	0.0438***	0.1620***
	(0.0148)	(0.0146)	(0.0145)	(0.0146)
Post Acquisition	-0.0021***	-0.0020***	-0.0017***	-0.0068***
	(0.0001)	(0.0002)	(0.0002)	(0.0023)
LLP BHC × (Size Acquired)/(Size BHC)	0.0419*	0.0873***	0.0899***	0.0792***
	(0.0248)	(0.0246)	(0.0225)	(0.0244)
Post Acquisition × (Size Acquired)/(Size BHC)	-0.0007***	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LLP BHC × Post Acquisition	0.1671***	0.1842***	0.1647***	0.1262***
	(0.0184)	(0.0179)	(0.0187)	(0.0187)
LLP BHC × Post Acquisition × (Size Acquired)/(Size BHC)	-0.1437***	-0.1641***	-0.1362***	-0.1466***
	(0.0349)	(0.0344)	(0.0337)	(0.0339)
Observations	56,024	56,024	56,024	53,425
R-Square	0.34	0.40	0.42	0.45
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
Bank Controls	-	-	-	Yes
State Controls	-	-	-	Yes

Table 7: Robustness Test - Sample Restricted to 1976 - 1995

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 1995 period. The dependent variable, *LLP Target*, corresponds to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.3310***	0.2032***	0.0710***	0.1842***
	(0.0170)	(0.0174)	(0.0170)	(0.0175)
Post Acquisition	-0.0016***	-0.0022***	-0.0016***	-0.0010
	(0.0002)	(0.0002)	(0.0002)	(0.0029)
LLP BHC × Post Acquisition	0.1768***	0.1895***	0.1394***	0.1199***
	(0.0211)	(0.0209)	(0.0215)	(0.0217)
Observations	40,344	40,344	40,344	37,959
R-Square	0.36	0.42	0.45	0.39
Acquirer FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
Bank Controls	-	-	-	Yes
State Controls	-	-	-	Yes

Table 8: Robustness Test - Matching Procedure

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, correspond to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. *Treated* is an indicator variable equal to one if a bank is acquired and zero for its matched counterpart. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.3058***	0.1762***	0.0386**	0.1659***
	(0.0172)	(0.0167)	(0.0154)	(0.0160)
Post Acquisition	-0.0005***	0.0001	0.0004**	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0018)
LLP BHC × Post Acquisition	0.0363	0.0326	-0.0050	-0.0114
	(0.0223)	(0.0208)	(0.0194)	(0.0198)
LLP BHC × Post Acquisition × Treated	0.1450***	0.1374***	0.1232***	0.1043***
	(0.0320)	(0.0303)	(0.0277)	(0.0288)
Observations	65,073	65,073	65,073	63,437
R-Square	0.34	0.41	0.40	0.37
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
Bank Controls	-	-	-	Yes
State Controls	-	-	-	Yes

Table 9: Robustness Test - Temporal Cut

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, corresponds to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. Columns (1) and (2) report the results for all acquisitions that took place before 1990. Columns (3) and (4) report the results for all acquisitions that took place after 1990. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.0607***	0.1142***	0.0528***	0.1761***
	(0.0215)	(0.0216)	(0.0206)	(0.0201)
Post Acquisition	-0.0016***	0.0046	-0.0018***	-0.0006
	(0.0002)	(0.0033)	(0.0002)	(0.0032)
LLP BHC × Post Acquisition	0.1507***	0.1911***	0.1661***	0.0710*
	(0.0252)	(0.0247)	(0.0392)	(0.0392)
Observations	32,567	30,251	23,578	22,904
R-Square	0.37	0.42	0.44	0.38
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	Yes	-	Yes	-
Bank Controls	-	Yes	-	Yes
State Controls	-	Yes	-	Yes

Table 10: Robustness Test - LLP Residuals

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target Residuals*, corresponds to the residuals of a model adapted from Beatty and Liao (2014) that estimate the level of loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the average loan loss provision residuals of all banking subsidiaries composing the acquiring BHC in the year before the acquisition, computed following the same model as the dependent variable. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target Residuals	(1)	(2)	(3)	(4)
LLP BHC Residual	0.2705***	0.1655***	0.0678***	0.1554***
	(0.0144)	(0.0153)	(0.0150)	(0.0152)
Post Acquisition	-0.0001	0.0001	0.0001	-0.0028
	(0.0001)	(0.0002)	(0.0002)	(0.0030)
LLP BHC Residual × Post Acquisition	0.1788***	0.1796***	0.1498***	0.1712***
	(0.0218)	(0.0216)	(0.0200)	(0.0215)
Observations	56,024	56,024	56,024	53,425
R-Square	0.34	0.40	0.44	0.39
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
State Controls	-	-	-	Yes

Table 11: Robustness Test - LLP Weighted

This table compares loan loss provisions of target banks to those of their acquiring bank holding companies over the 1976 - 2005 period. The dependent variable, *LLP Target*, corresponds to the loan loss provision of target banks. *Post Acquisition* is an indicator variable that equals one after the acquisition of a target bank by another BHC, and zero otherwise. *LLP BHC* is equal to the *weighted* average loan loss provision of all banking subsidiaries composing the acquiring BHC in the year before the acquisition. We use subsidiary size as a weighting criterion. All other variables are defined in Appendix A. Standard errors are clustered at the acquisition level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable: LLP Target	(1)	(2)	(3)	(4)
LLP BHC	0.2911***	0.1696***	0.0506***	0.1525***
	(0.0127)	(0.0125)	(0.0121)	(0.0125)
Post Acquisition	-0.0019***	-0.0018***	-0.0015***	-0.0062***
	(0.0001)	(0.0002)	(0.0002)	(0.0023)
LLP BHC × Post Acquisition	0.0971***	0.1233***	0.1203***	0.0792***
	(0.0155)	(0.0153)	(0.0155)	(0.0159)
Observations	56,145	56,145	56,145	53,497
R-Square	0.35	0.42	0.46	0.40
Acquisition FE	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	Yes
State-Year FE	-	-	Yes	-
Bank Controls	-	-	-	Yes
State Controls	-	-	-	Yes

3.8 Appendix

Appendix A: Variable Definition and Sources

Variable Name	Variable Construction	Source
LLP	Loan loss provision (item *riad4230*) over total loans (item *rcfd2122*)	FED Call Report
Post Acquisition	Indicator equal to one after the acquisition date, and zero otherwise. Acquisitions are identified using changes in ownership (item *rssd9348*)	FED Call Report
Log(Assets)	Logarithm of banks' total assets (item *rcfd2170*)	FED Call Report
Loan Growth	Growth rate of banks' total loans (item *rcfd2122*)	FED Call Report
Loan Concentration	HHI of the following loan categories: real estate loans (item *rcfd1410*), agricultural loans (item *rcfd1590*), C&I loans (item *rcfd1600*) and loans to individuals (item *rcfd1975*)	FED Call Report
Non-Performing Loan Growth	Growth rate of banks' non-performing loans, computed as the sum of items *rcfd1403* and *rcfd1407*	FED Call Report
Size Ratio	Ratio of acquiring BHC's total assets to target BHC's total assets the quarter preceding the acquisition. BHC's total assets are the sum of total assets (item *rcfd2170*) of all existing subsidiaries.	FED Call Report
Population	Log of total population	BEA
Personal Income	Average state personal income	BEA
Personal Income Growth	Change in yearly personal income	BEA
Same MSA	Indicator equal to one if the acquiring and target banks are in the same metropolitan statistical area, (item *rssd9180*), and zero otherwise	FED Call Report
(Size Acquired) / (Size BHC)	Ratio of target BHC's total assets over acquiring BHC's total assets on the quarter preceding the acquisition BHC's total assets are the sum of total assets (item *rcfd2170*) of all existing subsidiaries.	FED Call Report.

Appendix B: Descriptive Statistics - Matching

This table presents the descriptive statistics for our sub-samples of acquired banks and matched banks. We construct our sub-sample of matched banks using a matching algorithm that minimizes the Mahalanobis distance between observations of pre-acquisition covariates. Bank characteristics are measured in the end of the year before the acquisition. We impose the requirement that target banks and their matched counterparts be located in the same state. We keep 2,779 unique acquisitions in this sample. The number of unique acquisitions in this sample is smaller than that of our main analysis because we require our matched sample of banks to be statistically comparable with acquired banks. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Acquired Banks (N= 2,779)			Matched Banks (N= 2,779)				
Variable	Mean	Median	Std Dev.	Mean	Median	Std Dev.	Difference	T-Statistics
LLP (%)	0.6092	0.3651	0.7434	0.5732	0.3582	0.6944	0.0370	(1.82)
Total Loan (Millions)	49.159	27.022	60.334	46.440	25.442	57.977	2.719	(1.64)
Loan Growth (%)	9.478	7.881	15.477	9.944	8.148	14.996	- 0.467	(1.09)
Leverage (%)	8.305	7.968	2.056	8.424	8.096	1.972	-0.119*	(2.01)

Conclusion

This PhD thesis is the result of five years of hard work inside HEC Paris finance department. It has been a pleasure and an honor to study there and to benefit from the presence and advices of ones of the brightest researchers in economics and finance. It also greatly benefited from my visiting at Harvard University where I found a perfect atmosphere to do research. The diversity of the topics covered in the three previous chapters reflect the various interests I have in finance. I am really grateful for all the things I learned, and sincerely hope that I will succeed in using that knowledge for a greater good.

Titre : Essais empiriques en finance

Mots clés : Crise de la zone euro, Secteur bancaire, Culture d'entreprise

Résumé : Cette thèse réalisée au sein du département finance d'HEC Paris est constituée de trois parties. La première s'intéresse à la résilience des chambres de compensation en temps de crise. C'est un travail réalisé avec François Derrien, Evren Ors et David Thesmar dans lequel nous montrons que le manque de régulation de ces acteurs conduit à une détérioration de la confiance qui leur est accordée quand les conditions macroéconomiques se détériorent. Ceci impacte alors négativement leur capacité à assurer une liquidité suffisante sur le marché interbancaire.

Le deuxième chapitre porte sur l'impact de la concentration du secteur bancaire autour de quelques grands groupes sur l'allocation macroéconomique du crédit. J'y développe une approche innovante pour répondre à cette question et montre que cet impact est limité: les chocs idiosyncratiques des "big players" n'ont qu'un rôle limité dans la fluctuation du crédit aggrégé.

La dernière partie est un travail réalisé avec Adrien Matray et Thomas Bourveau. Nous nous intéressons à la transmission de la culture du risque au sein du secteur bancaire et montrons que les filiales d'un groupe bancaire tendent à converger quant à leur évaluation du risque futur. En retour, cela peut amener à une sous-évaluation de ce dernier et impacter la stabilité financière.

Title : Empirical essays in finance

Keywords : Eurozone crisis, Banking, Corporate Culture

Abstract : This thesis is divided into three chapters. The first one deals with Central Clearing Counterparties (CCPs) and their resiliency in crisis times. This is a joint work with François Derrien, Evren Ors and David Thesmar. Focusing on CCPs backed repo trades during the eurozone crisis, we show that the market factored in the default of CCPs. In turn, this affected their capacity to ensure liquidity in the interbank market. Our results have strong consequences for the way CCPs should be regulate.

The second chapter aims at quantifying the impact of the rise of the concentration in the banking sector on aggregate credit fluctuations. Building on novel empirical approach, I show that big players' idiosyncratic shocks have a limited impact on aggregate credit. The explanation lies in the fact that the strength of banking groups idiosyncratic shocks is limited compared to aggregate and subsidiaries level ones.

The last chapter, a joint work with Thomas Bourveau and Adrien Matray, focuses on the transmission of corporate risk culture. We show that subsidiaries of the same banking group tend to assess future risks in similar ways. In turn, this gives insights on how banking crisis can spread be fueled by corporate risk culture.